A prediction horizon in control technique of the DC-DC boost converter based on DLMNN

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Abstract: Model Predictive Control (MPC) algorithms are regarded as computationally intensive optimization based control methods. Their complexity elevates when the cost function Prediction Horizon (PH) augments. This problem is more prevalent when implementing this technique to systems with fast dynamics and in this case, the PH length is restricted by the processor's computational power. This paper proposed a PH in the control method of the DC to DC boost converter centered on Deep Learning Modified Neural Network (DLMNN). The Finite set control (FCS) -MPC scheme is employed in this proposed method. Here, the DC to DC boost converter state-space model and the proposed control technique are individually explained. Using the DLMNN approach, the optimal PH is effectively selected. The weight values of every single neuron layers in the DLMNN are optimized with the utilization of the Cuckoo Search Optimization (CSO) algorithm. Lastly, the proposed system's performance is analyzed. The outcomes show the high-level performance of this proposed system.

Key words: *Deep Learning Modified Neural Network (DLMNN), Cuckoo Search Optimization (CSO), Finite Set Control Model Predictive Control (FSC-MPC and DC-DC boost converter.*

1. INTRODUCTION

The control of power electronic converters is a hard task on account of their hybrid or switched non-linear feature. The standard control method averages the continuous-time dynamics related to the disparate operation modes and linearizes them at the operating point [1]. Lately, the dc to dc conversion has improved into a ubiquitous technology, which is utilized in disparate applications, encompassing dc motor drives and dc power supplies [2]. Certain researchers paid attention to the development of boost dc to dc converter with higher voltage gain [3]. Manifold impedance networks are being proposed for enhancing the power conversion with higher voltage gain. MPC stands as an effectual strategy for controlling several applications in innumerable industries [4].

During the 1970s, MPC was built in the process control industry and is now being used in the field of power electronics [5]. This encompasses 3-phase ac-dc and dc-ac systems and also dc to dc converters [6]. The prime advantage of MPC is the characteristic that it could stabilize linear or nonlinear systems under the hard state as well as input constraints [7]. In MPC [8], the control is attained by resolving the optimization problem online using a provided Objective Function (OF) over a finite PH under a discrete-time model and constraints of this system. The PH [9] is the chief problem in an MPC because when the PH is high, the computational cost becomes high. For picking-out optimal PH as of diverse PH values, the research works used disparate algorithms [10].

The draft structure for this paper is systematized as: Section 2 surveys the associated works regarding the method proposed. Section 3 briefly discusses the proposed methodology, section 4, explore the Investigational outcome and section 5 infers the paper.

2. RELATED WORK

Mahlagha Mahdavi Aghdam *et al.* [11] presented a 2-step PH algorithm of the MPC approach for grid-tied inverters utilized in wind turbines. The control objectives like reactive and active power flow as well as switching loss reduction were evinced in the OFs of a controller. The MPC was validated numerically by employing it in the MATLAB/Simulink.

Sergio Lucia *et al.* [12] put forward a deep learning-centric MPC for the resonant power converters (RPC). The approach was utilized for learning offline the optimum control policy proffered by a complex predictive formulation model grounded on deep neural networks (NNs) in order that the online utilization of the learned controller needed only the assessment of a NN. The attained learned controller was executed quickly on the embedded hardware. The outcomes evinced the potentiality of the proffered approach on a Hardware-in-the-Loop setup of a Field Programmable Gate Array (FPGA)-controlled RPC.

Ihab S. Mohamed *et al.* [13] recommended a control method for a 2-level converter grounded on combined feed-forward ANN and MPC. Initially, MPC was utilized during training for generating the data needed for training the propounded NN. Then, the NN was fine-tuned and hence it could be utilized online mainly for voltage tracking without utilizing MPC. In experiential evaluation, the performance proffered by the ANN-centric controller was assessed on multiple samples of linear and also nonlinear loads under disparate operating states. It evinced that the ANN centered control approach has pre-eminent dynamic and steady performance when contrasted to that of MPC.

Tobias Geyer *et al* [14] rendered a medium-voltage drive system with an LC filter and induction machine, a direct MPC algorithm (with no modulator) with extremely long PHs. The MPC regulated the capacitor voltage, stator current and inverter current along the provided references simultaneously. The PH notably diminished the oscillations on account of the filter resonance. For amply long PH (ten), a lower total harmonic distortion of stator current was attained at lower device switching frequencies. A supplementary active damping loop was unnecessary but it was added for the conceptual simplicity of a control method.

3. PROPOSED METHODOLOGY

MPC acquired numerous developments and extensive applications in disparate industries amid the last 40 years. For the early MPC strategies, the control performance and applications remained a big challenge. Grounded on such backgrounds, state-space models comprise more system-related information on the controlled system when contrasted to the conventional models. Generally, constant PH is utilized in control methods. A large PH augments performance and it significantly elevates the computational cost. Therefore, PH is chosen to be just long enough to get the needed performance. This paper proposed a PH in control technique of the DC to DC boost converter based on the DLMNN approach. This paper pays attention to the state-space model of the DC to DC boost converter. Here, the state-space models of the DC to DC boost converter as well as the FCS-MPC are described individually. The optimal PH is picked centered on the DLMNN approach. The blocks in Figure 1 give a detailed explanation of the proposed system.

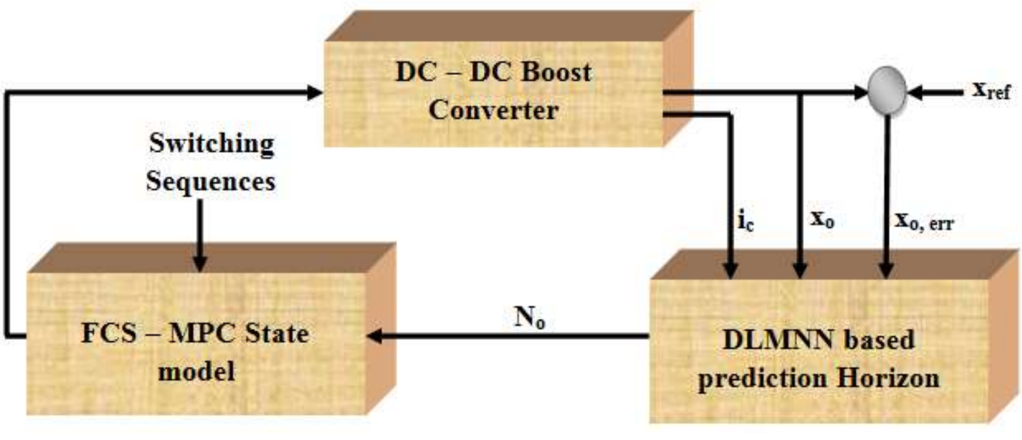


Figure: Block diagram for the proposed prediction horizon

3.1 State models of the DC-DC boost converter

DC-DC converters have extensive applications namely, DC motor control, DC power supplies, renewable energy systems, hybrid electrical systems, and electric vehicles. The DC-DC converters bring the need of controlling the converters in desired scenarios. The model is signified in the state space form as:

$$u(k+1) = M_S\, u(k) + I_S\, x_s(k) \tag{1}$$

$$v(k) = O(u(k)) \tag{2}$$

Where, $u(k) = [i_c(k)\; x_0(k)]$ indicates the state vector comprising the output voltage x_0 and inductor current $i_c(k)$, x_s signifies the supply voltage of the converter, k denotes current time step, whereas, M_S and I_S denotes the matrix of the state space that are reliant on the sampling interval S_i. S signifies various operation modes of the boost converter and could take the value as of the set {1, 2, 3, 4} relying on the switch state {0, 1} and the inductor current (zero or non-zero). The output of the model is symbolized by $v(k)$. The matrix O indicates the output matrix of the system.

3.2 Finite control set model predictive control

Here, the control scheme of the MPC is expounded. Next, the significance of the large PH is found and then the load is changed. The MPC scheme utilizes an enumeration method that ascertains the actuation of the switch for controlling the output voltage. The OF is:

$$F_q = \sum_{f=k}^{k+N-1} \left| x_{ref} - x_o(f) \right| + \eta \left| y(f-1) - y(f) \right| \tag{3}$$

Where, N indicates the PH over which the variables of interest are penalized, x_{ref} signifies the Reference Voltage (RV), and y denotes the switch position (on or off) and η signifies the weighting factor. The 2nd term of the OF is utilized to avert excessive switching and lessen the switching frequency.

The FCS-MPC computes the optimal sequence as of all probable switching sequences over N. In enumeration, the OF cost F_q is assessed for all sequences. The sequence which returns the lowest cost is regarded as the optimal sequence. The optimal switch position which is the first entry of this optimal sequence is then employed to the converter. This whole process is done in the sampling interval S_i. It is repeated at every step centered on the newest values of the model states.

The boost converter exposes a non-minimal phase behavior that entailed an initial drop in the output voltage when the RV is elevated. This behavior needs a large PH for seeing the eventual elevation of output voltage once it drops. A large PH also enhanced the converter's physical performance in the transient state where it aids to attain the RV in less time. The load is time-varying in several applications.

3.3 Prediction horizon method

In this scheme, the PH is kept constant. An increase in PH increases both physical performance and computational complexity. The purpose of the proposed method is to ascertain a PH that provides a trade-off between physical performance and low computational complexity. This paper has a varying PH that adapts itself to the changing values of i_c, x_0 and $x_{0,err}$ during disturbances in load, changes in output RV, transients and steady-state. The PH is based on the cyber-physical cost function. The cyber-physical cost function is grounded on the total of physical performance that means, the OF F_q is added with the weighted cyber utilization F_t and is expressed as,

$$F_{qt} \coloneqq F_q + \lambda F_t \tag{4}$$

Where, λ indicates the weighting factor in-between the physical and cyber costs. The F_t value elevates with N. Therefore, a trade-off has to be found between cyber utilization and physical performance. The optimal PH, N_0, lessens the cost F_t over N. In this proposed methodology, the optimal PH is determined by implementing the DLMNN which was expounded below.

Since the existing Artificial NN (ANN) has just '1' hidden layer (HL), it takes more time for training the data. To resolve this, the proposed method uses more than '3' HLs and generates optimized weight value in-between the input layer (IL) and HLs, HL and output layers (OLs) utilizing the CSO algorithm, which is termed as DLMNN. The DLMNN's structure is provided in Fig 2,

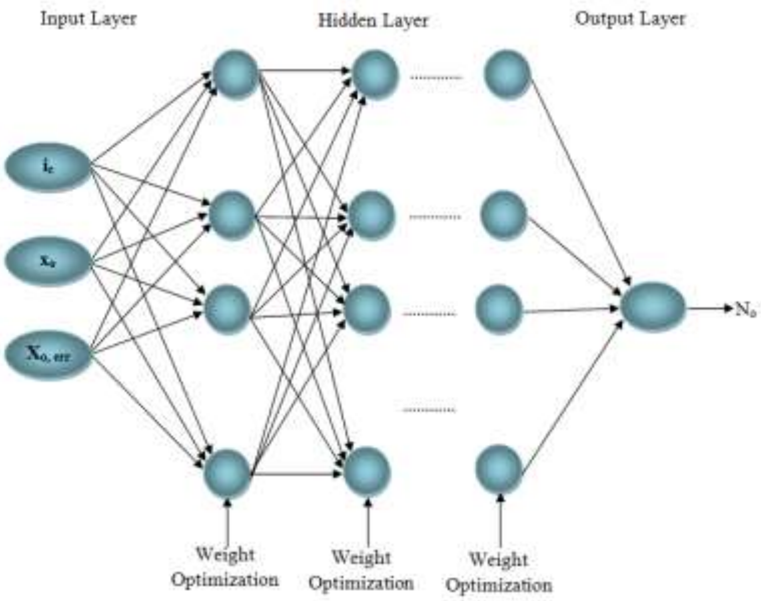


Figure 2: Structure of the DLMNN

The proposed DLMNN has an IL, an HL, and OL. The IL has a converter i_c, x_o, and the error between the RV and the output voltage $x_{o,err}$. The output of the NN is the optimal PH N_o, corresponding to the inputs. The DLMNN forms an input function of the IL, adaptive N, as follows:

$$N_o = addaptivN(i_c, x_o, x_{o,err}) \tag{5}$$

The HL is a layer that is hidden in between IL and OLs. The HLs perform computations on the weighted inputs and produce net input, which is then applied with activation functions to generate the actual output. Initially assign all the weights that are needed for the functioning of the algorithm. In the final stage, the OL is obtained by the calculation of activation function, which is expressed as follows,

$$N_o = A_s + \sum_{i=1}^{n} D_i \,.\, W_i \tag{6}$$

Where, N_o indicates the output unit, A_s denotes the bias, D_i represents the HL unit and W_i signifies the weight value. The HL output is evaluated as follows,

$$H_i = A_s + \sum_{c,o,i=1}^{n} (i_c, x_o, x_{o,err}).\, W_i \tag{7}$$

Assess the error function of the output utilizing the subsequent equation.

$$E(l) = (F_q - O_s) \tag{8}$$

Where, $E(l)$ indicates the error signal, O_s is the output signal and F_q signifies the target output of the DLMNN that means the OF is denoted as the targeted output. The error of the system is ought to be minimized. To achieve this, the difference betwixt the target and the attained output must be less. To minimize this value, the weights must be optimized. In the proposed system, optimization is acquired by utilizing the CSO algorithm, which is explained in the subsection.

3.3.1 Cuckoo Search Optimization (CSO) algorithm

The CSO is adapted as of swarm intelligence notions and inspired by cuckoo birds. Cuckoo birds normally lay eggs not on their nests but on other bird's (host) nest. The cuckoo morphs its egg similar to the other bird's eggs. This has to be done in order that those eggs are not killed or destroyed by the host (owner) since its eggs have no resemblance to the owner's egg. If the cuckoo birds' eggs are undetected by the host, then they will hatch and become birds with instincts.

The algorithm is as well influenced by the Levy flight (LF) nature of specific birds. Once a cuckoo lays its eggs in host bird nest, the host might come to know, that these are not their eggs. In that case, the host may either kill them or leave them. Three conceptual rules for the simple description of the CSO are listed below:

- Each cuckoo lays an egg at a time and dumps it in an arbitrarily chosen nest.
- The best nests having the best quality eggs (solutions) would be taken to the subsequent generations.
- The number of existing host nests is now fixed. A host could discover an unknown egg with probability $P_a \in [0,1]$.

Subsequently, for a cuckoo i, the new cuckoo (solutions) $h_i^{(t+1)}$ is generated with the utilization of LF as:

$$h_i^{(t+1)} = h_i^{(t)} + \alpha \oplus Levy(\omega) \tag{9}$$

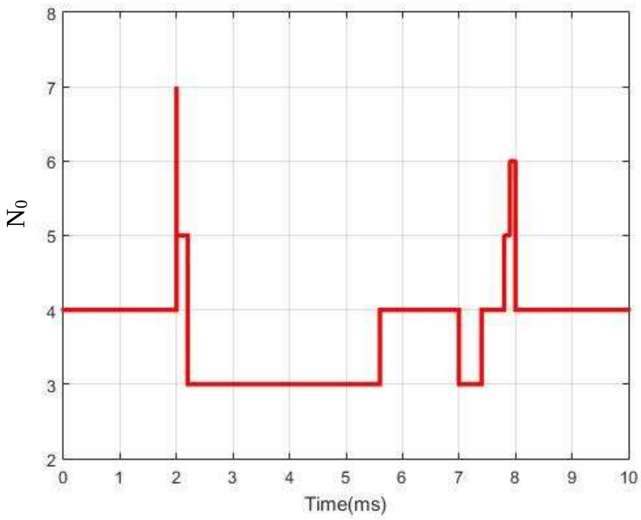
Here, $\alpha > 0$ indicates the step that is adjusted to the problem scales, whereas, the product $\oplus$ indicates entry wise multiplication. The LF signifies a random walk wherein the random step length is evaluated from Lévy distribution for large steps as:

$$Levy \sim r = t^{-\omega}, \qquad (1 < \omega \leq 3) \tag{10}$$

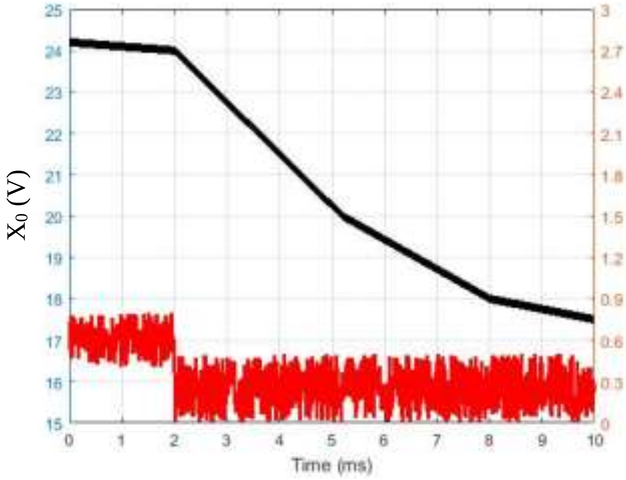
Where, ω indicates the levy distribution function. The above equation (10) has an infinite variance with an infinite mean. At this point, a random walk course which is the consecutive steps or jumps of a cuckoo follows the power-law step-length distribution with a grave trail.

4. RESULT AND DISCUSSION

The performance shown by the proposed system is analyzed in this section. Employ the proposed PH of the DC to DC boost converter based on DLMNN in the MATLAB/Simulink. The reference output voltage down and up analyses are evinced in the below figures.



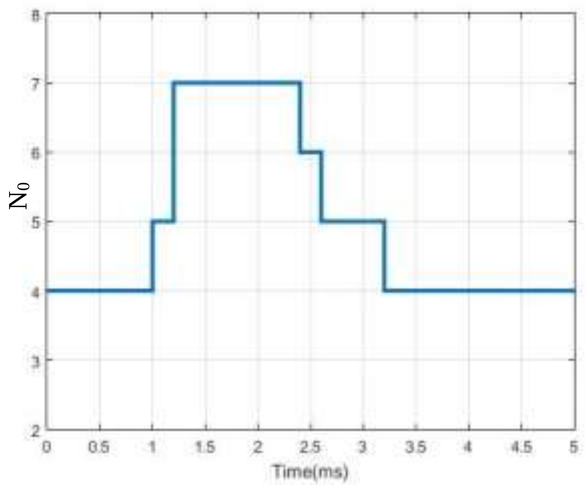
(a)



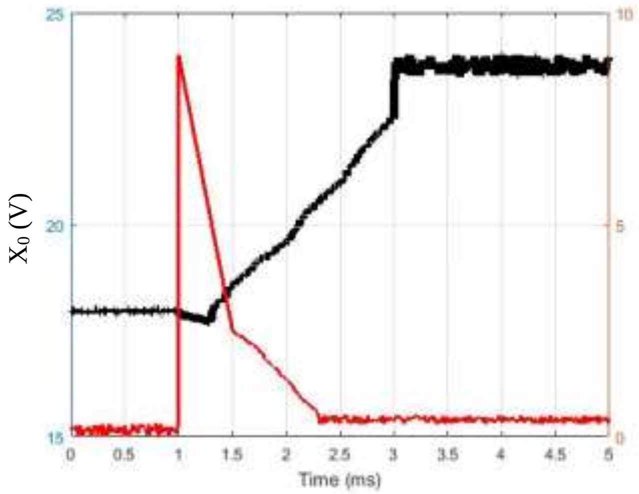
(b)

Figure 3: down reference output voltage of the proposed system

Figure 3 elucidates the down reference output voltage of the proposed PH system. A down change in the reference output voltage was applied to perceive the behaviors of output voltage and inductor current in the case of PH. During the step-down change from 24 V to 18 V, the PH adapts to smaller values when the capacitor is discharging.



(a)



(b)

Figure 4: up reference output voltage of the proposed system

Figure 4 delineates the up reference output voltage of the proposed PH. An up change in the reference output voltage as of 18 V to 24 V causes the PH to adapt to a huge value during transients. After reaching the steady-state, the PH falls back to a smaller value.

5. CONCLUSION

MPC is an advanced control method utilized to handle uncontrollable systems with the utilization of the classic control schemas. This MPC is utilized in several industries. While utilizing the MPC, the PH proffers the higher performance and lower computational cost. For improving the PH, this paper proposed a PH of control technique of the DC-DC boost converter based on the DLMNN technique. The PH is chosen grounded on a cyber-physical cost that permits diminishing the computational cost as a trade-off to physical performance. In the proposed system, the computational complexity is an exponential function of N, the reduction of N amid steady-state brings a significant reduction in the overall computational complexity.

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