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***Abstract*—In the past years model predictive control (MPC) has received a lot of attention in the power electronics field. Due to very simple inclusion of the control objectives and straightforward design, it has been adopted in a lot of different converter topologies. However, computational burden often imposes limitations in the control implementation if multistep predictions are deployed or/and if multilevel converters with many possible switching states are used. To remove these limitations, we propose to imitate the predictive controller with computationally light signal-processing structure that achieves comparable performance as the original controller. Our proposed imitator is an artificial neural network (ANN) trained offline using data labelled by the original MPC algorithm. Since the computational burden of the imitator is not correlated with the complexity of the MPC algorithm it emulates, implementation of much more complex predictive controllers is made possible without prior limitations. The proposed method has been validated experimentally on a stand-alone converter configuration and the results have confirmed a good match between the imitator and the predictive controller performance. Simulation models of both controllers are provided in the supplementary files for three different prediction horizons.**

***Index Terms*—Artificial neural networks, control design, DC-AC converters, finite-set model predictive control, supervised imitation learning.**

I. Introduction

THE idea of using the artificial neural networks (ANN) for power electronic control systems was considered already in the early 90's [1], [2]. One of the main reasons why this idea was pursued is the capability of ANN to process complex signals in a short time. Due to its parallel structure, the computational burden was lower then for the conventional controllers which were limiting the switching frequency of the converters. Moreover, the idea of having a controller that could adapt to the changing environment conditions was considered very attractive. Already in 1994, the authors of [3] reported an online-trained neural network on a DC-DC boost converter with experimental validation. Later, with further advances in microprocessor technology, more ANN based controllers were proposed in power electronic control systems [4]–[6].

In this paper we extend the concept of using ANN as a controller imitator for the finite-set model predictive control (FS-MPC). FS-MPC is an advanced control method that has gained a lot of attention in recent years due to its straightforward design, simple inclusion of different objectives and its discrete nature that is natural for control of power converters [7]. Thus, it was not a surprise that FS-MPC has been adapted very quickly to various topologies of power electronic converters [8]. However, there is still one limitation that is stopping the potential of FS-MPC in power electronics. Namely, multi-step horizon prediction algorithms or the applications on multilevel or multicell converters are still limited due to the large computational burden. As the FS-MPC has to perform a number of iterative calculations to find the optimum voltage vector, the more voltage vectors one topology has, the more calculations are needed. Similarly, for multi-step prediction horizons, the number of candidate switching options is increasing exponentially.

Therefore, many simplifications in the form of sorting algorithms, extrapolations and cost function modifications were necessary in practical implementations to reduce the number of candidate switching states. In [9] the authors have proposed a reduced complexity MPC for multi level converter topologies where DC-link voltage balancing was removed from the cost function and in [10] the authors have split the control objectives in two stages for MMC application. These solutions are sacrificing performance to reduce the computation burden. Simplifications necessary for reducing the candidate switching states for prediction and evaluation in the cost function for a matrix converter are presented in [11]. A sorting algorithm is another way to reduce the number of the candidate switching options in MMC applications [12]. Multi-step prediction horizon algorithms have shown a great potential in drives application but they can not be implemented without sorting algorithms and extrapolations to reduce the complexity [13], [14].

The approach presented in this paper does not require modifications of the conventional FS-MPC algorithm or design of a heuristic search algorithm. Using the ANN, an accurate imitator of the conventional FS-MPC algorithm can be created. As it will be shown experimentally, the key advantage of the imitator compared to standard controllers is that its execution time is independent of the complexity and prediction horizon of imitated controller. Namely, it depends only on the number of neurons in the network. Compared to the deep neural network approach in [6], in our approach only one hidden layer is necessary to control all the switches in the converter topology. Moreover, the presented design approach can produce an ANN imitator with much higher accuracy then in [6]. This is confirmed both in simulations and experiments. We also present a novel data generation process, which allows quick and comprehensive covering of the controller's actuation space.

II. System model

Supervised imitation learning approach in this paper is demonstrated on a stand-alone VSC with an LC output filter and a resistive load. This converter configuration can typically

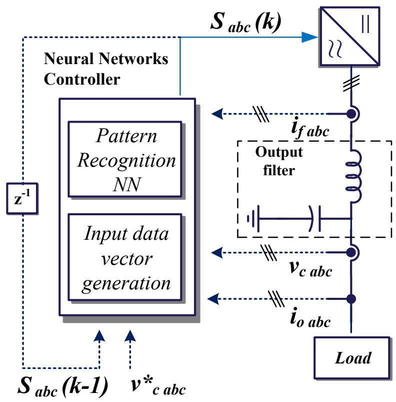


Fig. 1: Simplified scheme of the control algorithm.

be found in the uninterruptible power supply (UPS) systems and AC microgrids. However, it is worth noting that proposed approach is general and can be applied to imitate any type of controller and any converter topology. The control algorithm needs to maintain a smooth sinusoidal output voltage and give a fast response under load variations. In Fig. 1, it is shown that for the implementation of the imitator controller, it is necessary to measure the filter currents $i_{f\,abc}$, capacitor voltages $v_{c\,abc}$ and load currents $i_{o\,abc}$. These measurements are also necessary for implementation of the conventional FS-MPC algorithm. Together with the previously applied voltage vector, these measurements are used to generate the input data vector for the pattern recognition neural network.

The imitator controller will learn to imitate the conventional FS-MPC algorithm presented in [15]. The FS-MPC algorithm uses the differential equations of the filter currents and capacitor voltages to calculate the future propagations of these variables:

$$\begin{bmatrix} \frac{di_f(t)}{dt} \\ \frac{dv_c(t)}{dt} \end{bmatrix} = \mathbf{A} \begin{bmatrix} i_f(t) \\ v_c(t) \end{bmatrix} + \mathbf{B} \begin{bmatrix} v_i(t) \\ i_o(t) \end{bmatrix} \tag{1}$$

where

$$\mathbf{A} = \begin{bmatrix} -\frac{R_f}{L_f} & -\frac{1}{L_f} \\ \frac{1}{C_f} & 0 \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} \frac{1}{L_f} & 0 \\ 0 & -\frac{1}{C_f} \end{bmatrix} \tag{2}$$

Before the implementation, the equations are discretized using the Euler forward discretization method with the sampling period of T_s = 20 μs. Following cost function is used in the algorithm:

$$g = \left(v^*_{f\alpha} - v_{f\alpha}\right)^2 + \left(v^*_{f\beta} - v_{f\beta}\right)^2 + \lambda_d \cdot g_d \tag{3}$$

$$g_d = \left(C_f \omega v^*_{f\beta} - i_{f\alpha} + i_{o\alpha}\right)^2 + \left(C_f \omega v^*_{f\alpha} + i_{f\beta} - i_{o\beta}\right)^2 \tag{4}$$

where $\bar{v}^*_f = v^*_{f\alpha} + jv^*_{f\beta}$ is the voltage reference vector, ω is the reference frequency and λ_d is the weighting factor of the additional current reference term. This term was proposed in [16] for improving the steady state performance of the algorithm and the weighting factor can be selected using the ANN approach in [17]. Table I shows system parameters used in the control algorithm.

TABLE I: System parameters

Parameter	Value
DC-link voltage	V_{dc} = 700 V
Output filter inductor	L_f = 2.4 mH, R_f = 0.1 Ω
Output filter capacitor	C_f = 14.2 μF
Algorithm sampling time	T_s = 20 μs
Weighting factor	λ_d = 1

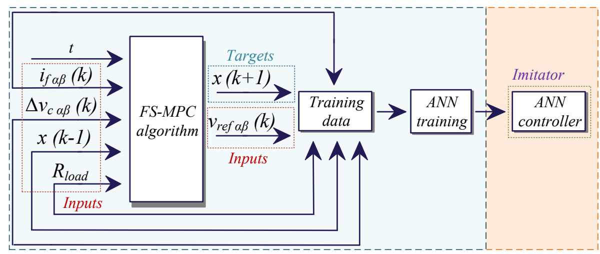


Fig. 2: ANN controller synthesis scheme.

III. Input data generation

The training data has a big influence on the quality of the ANN and special attention is thus given to generation of the training data. In particular, we show that it is not necessary to run a simulation model of the system to generate the data. In contrast, we only use the FS-MPC algorithm function. This allows us to quickly generate vast amounts of data that ensures comprehensive coverage of the controller's action space. We have generated an input matrix of more than 140 million data vectors in only 3 minutes on paralleled CPUs. As shown in Fig. 2 the FS-MPC algorithm accepts 7 input values: time (t), filter currents ($i_{f\,\alpha}$, $i_{f\,\beta}$), capacitor voltage deviations ($\Delta v_{c\,\alpha}$, $\Delta v_{c\,\beta}$), optimum voltage vector from previous sampling period $x(k-1)$, load resistance (R_{load}) and calculates 3 output values: reference values ($v_{ref\,\alpha}$, $v_{ref\,\beta}$), and future optimum switching combination $x(k+1)$. The reference values $v_{ref\,\alpha\beta}$ are not used in the inputs because the two values are coupled and to keep this dependency it is more convenient to use time vector as an input value. They are calculated using two sine wave equations with a 120° phase shift and the input value of the time vector t.

Following input data was used in the example presented in this paper: time vector $t = [0 : 0.002 : 0.018]$, filter current vectors $i_{f\,\alpha\beta} = [-16 : 3 : 16]$, load vector $R_{load} = [30 : 5 : 60]$, optimum voltage vector from previous sampling period $x_{old} = [1 : 1 : 7]$ and difference between the measured and the reference capacitor voltage vectors $\Delta v_{c\,\alpha\beta} = [-5 : 1 : 5]$. These input vectors form a matrix so all possible combinations are evaluated by the FS-MPC algorithm.

IV. Imitator performance

To obtain the imitator, we used a pattern recognition method. The output of the ANN controller, i.e. the *Target*, is a vector with 7 elements. The position of the value 1 in the output vector defines the selected optimum voltage vector. For example, target vector $x(k+1) = [0010000]$ defines the

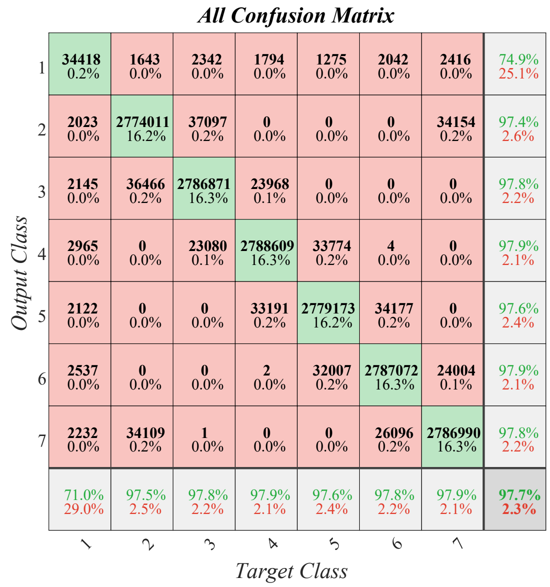


Fig. 3: Confusion matrix of the performed ANN training showing the number of correctly (green) and incorrectly(red) classified observations.

voltage vector V_3. To train the network with 8 input neurons, 15 hidden neurons and 7 output neurons, Neural network pattern recognition app was used. 70% randomly divided input data was used to train the network and 15% for validation and testing. Scaled conjugate gradient back-propagation algorithm [18] is used to train this type of neural networks. Performance of the training can be observed in the confusion matrix, which is shown in Fig. 3. It can be seen that each row in the matrix corresponds to the predicted class, and the columns correspond the true class, i.e the Target class. The cells in the diagonal of the matrix show how many observations were correctly classified, while all other cells show the incorrect classifications. In the presented example we can see that 97% of the observations were correctly classified. Therefore, we can proceed to the next step and export the trained ANN to Simulink model.

Before the imitator was implemented in the dSPACE real-time platform, a set of simulations was performed to compare the performance with the conventional FS-MPC algorithm from which the imitator was derived. The results have shown that using the imitator a voltage total harmonic distortion (THD) of 1.42% was obtained, while the conventional algorithm showed a THD of 1.33%. Moreover, average switching frequency was also obtained for the two controllers. The imitator was operating with average frequency of 8 kHz and the conventional algorithm with 8.6 kHz. These performance metrics show that the imitator is capable of imitating the behaviour of the conventional algorithm on a very high level. Simulation models for both the conventional and imitator controller are provided in the supplementary files for horizon prediction 1, 2 and 3. The reader can thus also check the good performance match for longer horizons.

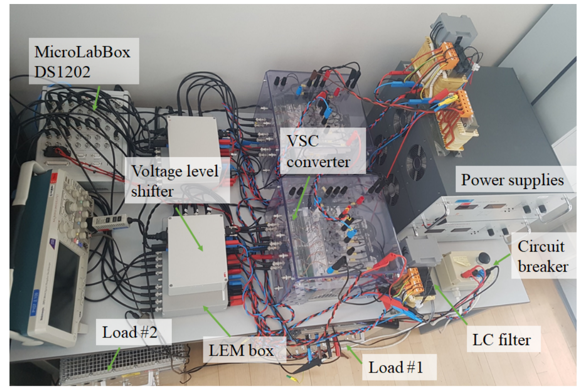


Fig. 4: Two level VSC experimental setup.

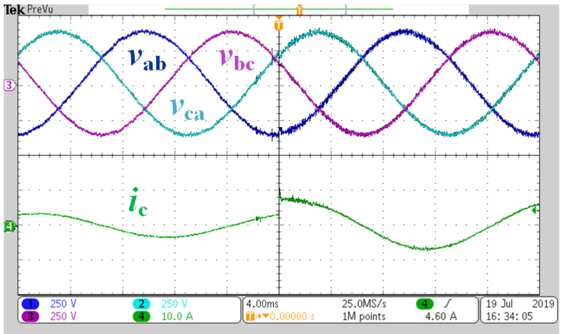
TABLE II: Performance metrics results from simulations and experiments for V_{cref} = 325 V and R_{load} = 60 Ω.

	Imitator controller		**Conventional controller**	
Perf. metrics	THD	f_{sw}	THD	f_{sw}
Simulations	1.42%	8 kHz	1.33%	8.6 kHz
Experiments	1.76%	7.6 kHz	1.69%	8.2 kHz

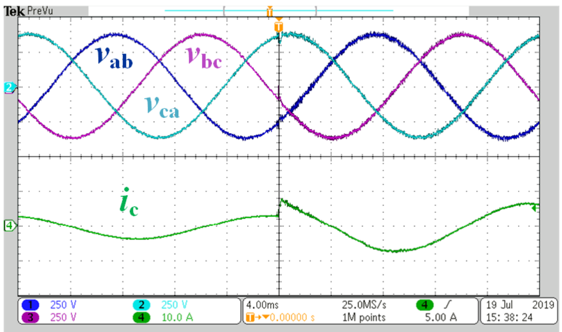
V. Experimental validation

For the experimental validation of the imitator and the conventional FS-MPC controller a MicroLabBox DS1202 PowerPC DualCore 2 GHz processor board and DS1302 I/O board from dSpace were used to implement the control algorithm. The experimental set-up is shown in Fig. 4 and the parameters match the simulation parameter values from Table I. The performance metrics in steady state operation for reference voltage V_{cref} = 325 V and R_{load} = 60 Ω were compared for both controllers in Table II. It is observed that the difference in the THD between the two controllers is 0.07% and for the switching frequency the difference is 600 Hz. This confirms very good learning performance of the imitator which was also obtained in the simulations. The higher THD in the experiments is a consequence of the converter dead time that was not implemented in the simulation model. The transient performance of the controllers was tested on a step load change R_{load} = 60 → 30 Ω and the results can be observed in Fig. 5. It is evident that the fast transient response of the FS-MPC was also successfully learned by the imitator controller.

The biggest impact of our proposed approach can be seen in the multistep prediction horizon FS-MPC. A comparison of the algorithm execution time and the horizon length for conventional and imitator model was performed in the Fig. 6. It can be noticed that the execution time for the imitator model is constant as it was not necessary to increase the number of hidden neurons to keep the same percentage of correct identifications in the confusion plot. In sharp contrast, the number of calculation is increasing exponentially for conventional algorithm, and an execution time under 20μs is not possible without overruns for 3-step prediction horizon (see Fig. 6).



(a)



(b)

Fig. 5: Step load transient R_{load} = 60 → 30 Ω: (a) imitator controller, (b) Conventional FS-MPC controller.

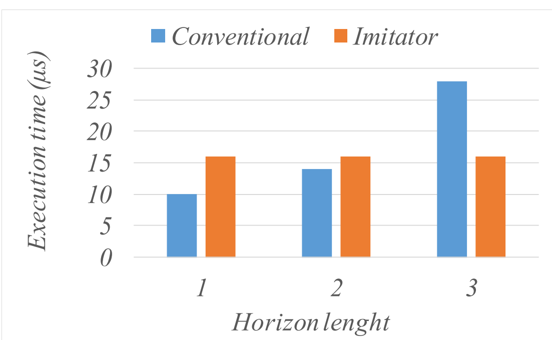


Fig. 6: Comparison of the algorithm execution time and the horizon length.

VI. Conclusion

The paper presented a new controller synthesis approach for power electronic converters. A neural network based imitator model of FS-MPC was trained using pattern recognition algorithm and successfully validated in experiments with a very good accuracy. Findings in this paper open many new possibilities for future development of the presented approach. From one point it gives an opportunity for implementation of computational heavy predictive algorithms with multi-step predictions or algorithms for multi-level or modular multi-cell topologies. Moreover, there is a possibility that the imitator could also be tuned online using the new measurements obtained during the operation. This would of course improve the performance of the controller even more. Therefore, future development of this approach could be of big interest also for the industry.

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