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Novak, Mateja; Grobelna, Iwona; Nyman, Ulrik; Blaabjerg, Frede

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Application of Statistical Model Checking for Robustness Comparison of Power Electronics Controllers

Mateja Novak
AAU Energy
Aalborg University
Aalborg, Denmark
nov@energy.aau.dk

Iwona Grobelna
Autom. Control, Electronics and Electr. Eng.
University of Zielona Góra
Zielona Góra, Poland
i.grobelna@iee.uz.zgora.pl

Ulrik Nyman
Department of Computer Science
Aalborg University
Aalborg, Denmark
ulrik@cs.aau.dk

Frede Blaabjerg
AAU Energy
Aalborg University
Aalborg, Denmark
fbl@energy.aau.dk

***Abstract*—Power electronic-based systems exhibit non-linear dynamics requiring simultaneous control of multiple control objectives. It is therefore expected that controllers that can cope with those nonlinearities will have a better performance than controllers requiring system linearization or nesting of the control objectives in a cascaded structure. However, the problem remains how to quantify their robustness and make a fair comparison between different non-linear controllers. The conventional tools used for the robustness validation of linear controllers cannot directly be applied to different non-linear controllers. Therefore, this paper demonstrates an approach based on statistical model checking for performing controller comparisons. The performance and robustness of different controllers (linear, model predictive, and neural networks-based) were compared in the same stochastic environment. Using this approach, a statistical estimate can be obtained for how the controller performance will be affected under different scenarios.**

***Index Terms*—Controller, hybrid automata, model predictive control, modelling, neural networks, power electronics, robustness, statistical model checking.**

I. Introduction

Linear controllers like proportional-integral (PI) or proportional resonant (PR) controllers are the most widely implemented control solutions in multiple power electronics-based systems (PES). Since the technology of these controllers is mature, methods for validating their robustness and stability are well-defined and extensively researched [1], e.g. root-locus, Bode plots and Nyquist stability criteria. In most industrial applications these controllers will be taken as go-to solutions [2]. However, since PES systems contain non-linear dynamics and have multiple control objectives, their performance will deteriorate if the non-linearities cannot be directly included or their bandwidth is limited due to the cascade control structure. On the other hand, non-linear controllers like model predictive control (MPC) are suitable for multiple-input multiple-output (MIMO) systems with complex nonlinear dynamics and they can provide a fast transient response [3]. Their initial limitation in PES was the computational burden, which through the increase of processing power in digital signal processing (DSP) units is no longer the major limiting factor for the implementation [4]. Both direct MPC and indirect MPC have been the focus of researcher for several years, to introduce design guidelines and methods to validate the robustness and stability [5]–[9]. The performance of model-based controllers is highly dependent on the model accuracy, thus robustness validation should not only be performed on disturbance impacts but also model parameter mismatch.

MPC-based methods are not the only methods considered as an alternative to linear controllers. One of the currently extensively researched controllers are based on machine learning methods such as feed-forward neural networks (NN) [10], [11]. Similar to the direct MPC, NN controllers might also suffer from a large computational burden if the network structure has several layers of neurons. Nevertheless, in recent publications, it was shown that approximating a control law of a multistep direct MPC controller does not require a large network structure to make the application feasible [12], [13]. The challenge for NN lies in the quality of the training data, which has to adequately represent the possible converter operating conditions. Moreover, when a linear controller is designed it is possible to directly assess the margins for the stable and robust performance, this is not straightforward for the NN controllers. Since the explainability of NN is still in the research stage [14], NN training performance metrics like Root Mean Squared Error (RMSE) do not necessarily lead to stable and robust performance once the NN is implemented in a PES system. Thus, there is a need for a method that would be able to quantify this performance.

To justify the use of non-linear control methods like MPC or NN in industrial PES, it is important to benchmark the method against the conventional control methods that are currently employed as demonstrated in [15] for motor-drives applications. The benchmarking typically includes an experimental comparison of steady-state performance and transient response in some operating conditions or a simulation study where parameters like switching frequency can be swept over a certain range to compare the harmonic distortion of the inverter output or compare semiconductor losses [15]. However, PES do not operate in deterministic operating conditions, typically the load is variable as well as the grid conditions. Thus, there remains the question of how operating conditions should be selected for comparison and how many iterations are required to obtain certainty of the desired performance.

This paper proposes the application of Statistical Model Checking (SMC) for robustness comparison of different linear and non-linear controllers in a stochastic environment. The modelling formalism used in this formal method is hybrid timed automata [16] that allow modelling of both deterministic and stochastic system dynamics, thus suitable for PES models. In this way, control methods that do not have analytical tools for robustness validation can be compared. Moreover, due to the presence of stochastic elements in the system and the degradation of components that influence the performance over time, the deterministic validation of robustness might miss potential critical scenarios that could lead to loss of system stability [17]. By applying an SMC approach, a statistical guarantee of the desired performance can be obtained. Herein, a case study is built around three controllers: a linear controller, a direct MPC controller, and an NN controller. The controllers are evaluated under the same stochastic load conditions in numerous simulations using the verification tool UPPAAL [16], [18]. Such extensive evaluation is usually not feasible in experiments, furthermore, the proposed method is faster and does not incur the risk of possible hardware damage.

The rest of the paper is structured as follows. Section II provides some information about the modelling formalism. Section III presents the specific models, their structures, advantages, and disadvantages. Section IV shows the results of performance validation both under stochastic load and model parameter mismatch. Finally, Section V summarizes and concludes the paper.

II. Modelling formalism

This paper utilizes the modelling and verification tool UPPAAL [18] to model and analyze three different control algorithms. UPPAAL is an integrated environment that supports modelling, validation, and verification of real-time systems. The models are prepared as networks of hybrid timed automata, which enables connecting individual components with each other. UPPAAL timed automata are a low-level modelling formalism in the sense that a lot of decisions are made by the engineer implementing the model, such as to what a time unit in an automaton model corresponds to in the real-world or what the boundary conditions are for the automata system making certain state transitions.

Since 2012 the UPPAAL tool has been extended with statistical model checking [16] of hybrid timed automata providing statistically valid results predicting system behavior. This functionality has great potential as it allows to directly evaluate different controllers (in this case: a linear controller, an FS-MPC controller, and an NN controller) under the same stochastic conditions. The hybrid timed automata models of UPPAAL can model both deterministic state-based behavior, non-linear behavior based on ordinary differential equations (ODEs), and stochastic behavior in the same models. The modelling language also includes a large subset of the C programming language, which made it trivial to port the NN to a UPPAAL model.

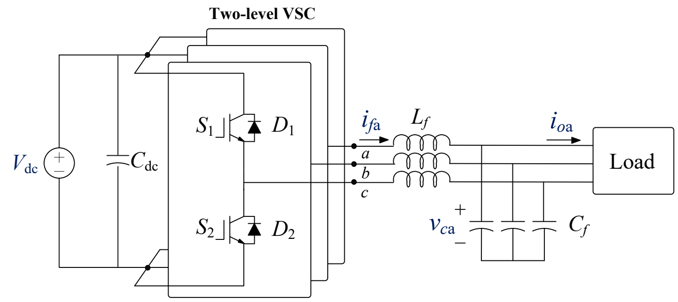

Fig. 1. Two-level voltage source converter in standalone operation used in this study for controller robustness validation.

TABLE I
SYSTEM PARAMETERS.

Parameter	Value
DC link voltage (V_{dc})	700 V
Filter inductance (L_f)	2.4 mH
Filter capacitance (C_f)	14 μF
Reference voltage ($V^*_{c\ rms}$)	400 V
Reference freq. (f^*)	50 Hz

Previous papers on performance verification using UPPAAL have validated individual controllers [7], [19]. In [20] the modelling process has been simplified and interfaces between components have been established. That allowed to build modular structures, easily adaptable to the particular area of application. Additionally, comparison of multiple converters or systems has become possible and the performance of the systems could be directly confronted. This paper goes one step further and evaluates the performance of three controller models by running them in parallel with the same physical system parameters and stochastic behavior of the load.

III. Controller structures

In this section the structures of three controllers will be introduced. These controllers were used to control the PES illustrated in Fig. 1 with the system parameters given in Table I. The system is a simplified version of a load-side converter used for standalone systems like uninterruptible power supplies (UPS) that typically have to deal with a variable load during the day. A two-level voltage source converter (2L-VSC) is used for this purpose and it is connected to a variable load through an LC filter to provide a low ripple voltage supply.

A. *Linear controller structure*

The linear controller selected for this case study is based on the controller proposed in [21] and depicted in Fig. 2. The controller structure consists of an inner current control loop with a propotional (P) controller, an outer voltage control loop with PR controller compensating the 5th and 7th harmonic (1),

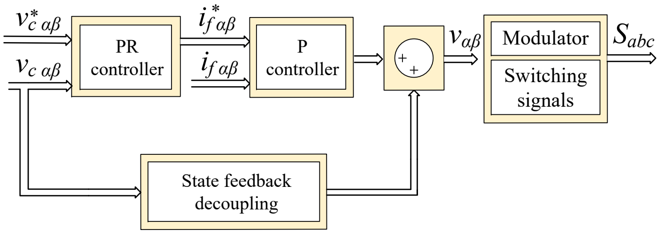

Fig. 2. Block diagram of the control structure using linear controller.

TABLE II
LINEAR CONTROLLER PARAMETERS.

Parameter	Value	Parameter	Value
k_{pI}	11.3	k_{pV}	0.05
k_{1V}	31.5	ϕ_1	3
k_{5V}	15	ϕ_5	37
k_{7V}	15	ϕ_7	44
τ_z	1.8e-4	τ_p	3.4e-5

which are typically associated with non-linear loads in UPS systems, and a state feedback decoupling path to compensate for system delays. The state feedback decoupling in (2) is designed as a first-order phase-lead compensator with a low-pass filter to reduce the effects of high frequencies and noise. The generated voltage reference $v_{\alpha,\beta}$ is then passed to the modulator block to obtain the pulse width modulation (PWM) signals for the semiconductor devices. The switching frequency is set to 10 kHz. For implementation, the load voltage ($v_{c\,\alpha\beta}$) and inverter current ($i_{f\,\alpha\beta}$) measurements are required. The design and tuning of the control parameters is performed according to the Nyquist criterion. Controller parameters are given in Table II. More details on designing the presented controller can be found in [21]. An example of a simulated run of a load step in a PES system with a linear controller is given in Fig. 3 where the voltage drop is visible during a load change.

$$G_v = k_{pV} + \sum_{h=1,5,7} k_{iV,h} \frac{s\cos(\phi_h) - h\omega_1 \sin(\phi_h)}{s^2 + (h\omega_1)^2)} \tag{1}$$

$$G_{dec} = \frac{1+\tau_z s}{1+\tau_p s} \cdot G_{LPF} \tag{2}$$

B. FS-MPC controller structure

The second controller used in this case study is based on Finite Set Model Predictive Control (FS-MPC) as proposed in [22]. The structure of the FS-MPC controller used herein is shown in Fig. 4. The advantage of FS-MPC lies in faster transient response due to the use of a single control loop but it also comes with a higher computational load due to iterative calculations that need to be used to evaluate the cost function for the finite set of voltage vectors that the converter can produce. Therefore it is necessary to compensate for the computational delay using the two-step predictions as

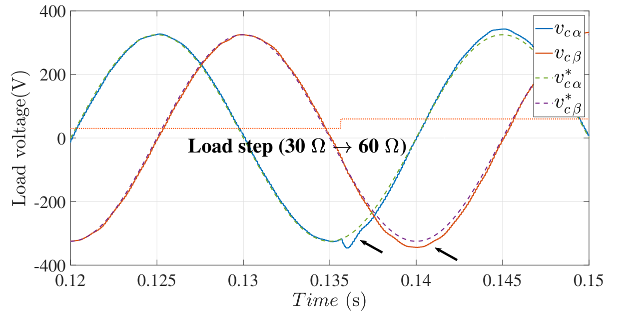

Fig. 3. Load step change in a PES with a linear controller recorded in the UPPAAL simulator.

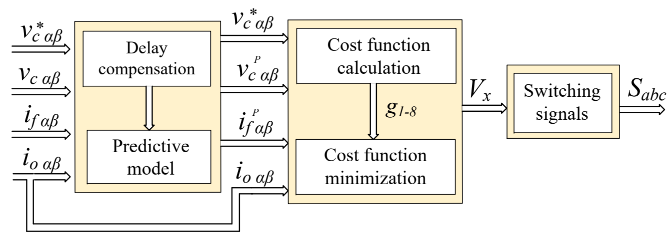

Fig. 4. Block diagram of the control structure using FS-MPC controller.

explained in [23]. The compensated value of load voltage ($v_{c\,\alpha\beta}$), inverter current ($i_{f\,\alpha\beta}$) together with load current ($i_{o\,\alpha\beta}$) (which can be obtained using an observer or a sensor) are used in the prediction model to obtain future values:

$$\frac{d}{dt}\begin{bmatrix} i_{f\,\alpha\beta} \\ v_{c\,\alpha\beta} \\ i_{o\,\alpha\beta} \end{bmatrix} = \begin{bmatrix} 0 & -\frac{1}{L_f} & 0 \\ \frac{1}{C_f} & 0 & -\frac{1}{C_f} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{f\,\alpha\beta} \\ v_{c\,\alpha\beta} \\ i_{o\,\alpha\beta} \end{bmatrix} + \begin{bmatrix} \frac{1}{L_f} \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} v_{i\,\alpha\beta} \end{bmatrix} \tag{3}$$

The predictions are compared to the reference values in the cost function proposed in [24] for obtaining low distortion load voltage in stand-alone converter applications:

$$g = (v^*_{c\alpha} - v^P_{c\alpha})^2 + (v^*_{c\beta} - v^P_{c\beta})^2 + \lambda_d \cdot g_d \tag{4}$$

$$g_d = (i^P_{f\alpha} - i^P_{o\alpha} + C_f \omega v^*_{c\beta})^2 + (i^P_{f\beta} - i^P_{o\beta} - C_f \omega v^*_{c\alpha})^2 \tag{5}$$

where L_f and C_f are filter parameters, v_i is the inverter output voltage, ω is the reference frequency, voltages and currents annotated with ^{P} are calculated predictions at $k+2$, while * defines the extrapolated reference voltage values, and parameter λ_d is the weighting factor and set to value 1.0.

Compared to the previously introduced linear control, the control signals are directly applied to the semiconductor switches without the use of a modulator. Thus, to obtain a fair comparison, the carrier frequency was adjusted to approximately fit the average switching frequency achieved on the converter system using the FS-MPC algorithm and NN controller. As mentioned in the introduction, model parameter mismatch will impact the performance of this controller, an example is given in Fig. 5 where 50% model parameter mismatch was simulated for a PES model in UPPAAL.

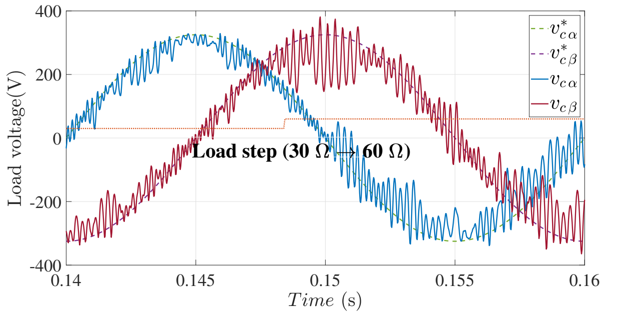

Fig. 5. Load step change in PES with FS-MPC and 50% error in the system parameters (L_f, C_f) recorded in the UPPAAL simulator.

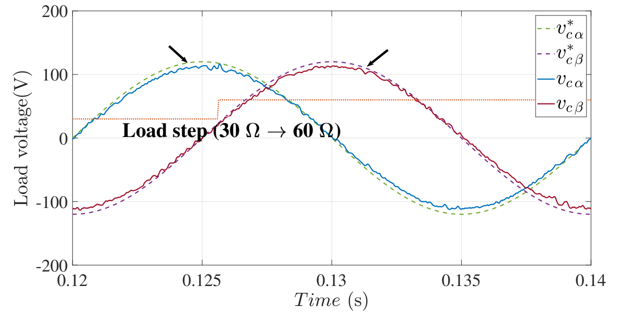

Fig. 7. Load step change in PES using NN controller with V_{dc} 50% lower than in training data recorded in the UPPAAL simulator.

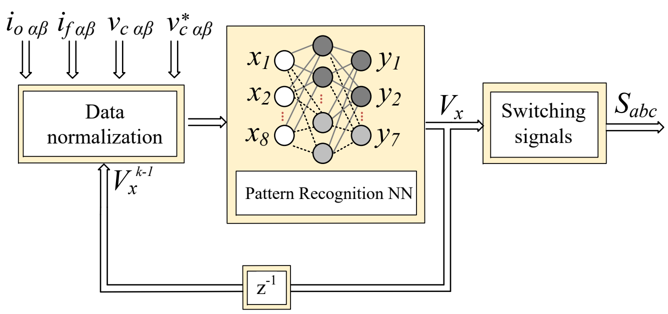

Fig. 6. Block diagram of the control structure of NN controller.

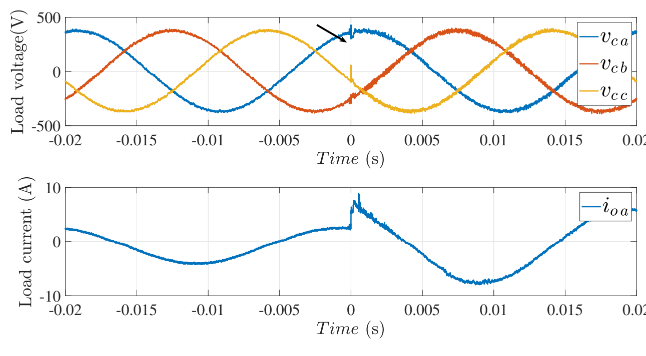

Fig. 8. Transient response of FS-MPC controller to load step 60Ω - 30Ω.

C. NN controller structure

The structure of the NN controller used in this case study is shown in Fig. 6. The controller was trained using the data generated by the FS-MPC controller with delay compensation presented in Section III-B, thus for operation it requires the same set of measurements as the original FS-MPC controller plus the information on the previously applied voltage vector. Imitating the control law of FS-MPC was defined as a pattern recognition problem, where each voltage vector of the inverter was defined as one class, with 7 in total. The structure of the NN was the following: 8 input neurons, 15 hidden neurons and a rectified linear unit (ReLu) activation function, and 7 output neurons with sigmoid activation function to obtain the one-hot coded optimal voltage vector. Similar to FS-MPC, the selected vector is applied for the whole sampling time. The adaptive moment estimation (Adam) optimization algorithm was used to obtain the parameters of the NN. An example of a simulation run performed in UPPAAL SMC with the designed NN controller is shown in Fig. 7, where the V_{dc} was reduced to more than 50% of the value used in the training data and the system could not reach the reference voltage.

IV. Performance validation

A load step change was performed in Fig. 8 and Fig. 9 on an experimental VSC set-up controlled by the FS-MPC and NN controllers described in the previous section. It can be observed that both controllers quickly respond to the load change with a low voltage dip. However, one such test cannot give much insight into the overall performance and it will be time-consuming to test different load step scenarios including also mismatched parameters. Therefore in this section, multiple simulation runs were conducted using SMC, where the RMSD (root mean squared difference) between the reference and load voltage was calculated $(\Delta V_\alpha, \Delta V_\beta)$. Examples of simulation runs are shown in Fig. 3, Fig. 5, and Fig. 7.

Before performing the performance comparison during load transients, the controllers were simulated in a system with nominal values and constant load to confirm that their performance is comparable (see Table III). The results for estimation of the maximal RMSD value for the three controllers with variable load 30→60Ω for both nominal conditions and with parameter mismatch are presented in Table IV and Fig. 10. The

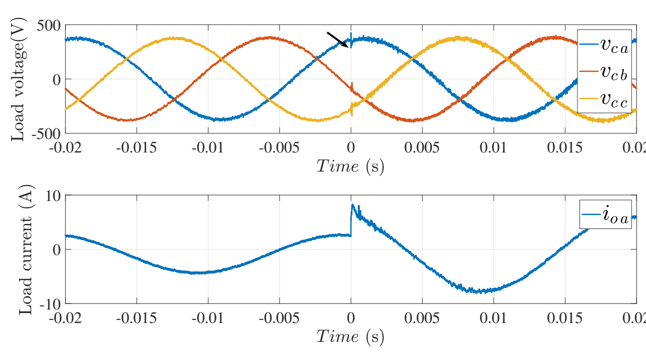

Fig. 9. Transient response of NN controller to load step 60Ω - 30Ω.

TABLE III
RESULTS FOR RMSD SIMULATION FOR THREE CONTROLLERS IN NOMINAL OPERATION WITH CONSTANT LOAD AND WITHOUT PARAMETER MISMATCH.

Load (Ω)	L error	C error	Vref ampl. (V)	Vdc (V)	Linear Controller	FS-MPC	NN
30	0	0	325	700	ΔV_α = 3.57 ΔV_β = 3.41	ΔV_α = 2.39 ΔV_β = 2.61	ΔV_α = 3.20 ΔV_β = 3.20
60	0	0	325	700	ΔV_α = 2.26 ΔV_β = 2.21	ΔV_α = 2.28 ΔV_β = 2.47	ΔV_α = 3.10 ΔV_β = 3.10

TABLE IV
RESULTS FOR ESTIMATION OF MAX RMSD FOR THREE CONTROLLERS WITH VARIABLE LOAD 30→60Ω
(NOMINAL CONDITIONS AND WITH PARAMETER MISMATCH).

Load (Ω)	L error	C error	Vref ampl. (V)	Vdc (V)	Linear Controller	FS-MPC	NN
30→60	0	0	325	700	ΔV_α = 9.07 +/- 0.34 ΔV_β = 9.50 +/- 0.26	ΔV_α = 2.56 +/- 0.11 ΔV_β = 2.83 +/- 0.07	ΔV_α = 3.31 +/- 0.10 ΔV_β = 3.37 +/- 0.14
30→60	0	0	120	700	ΔV_α = 4.03 +/- 0.15 ΔV_β = 3.92 +/- 0.14	ΔV_α = 1.79 +/- 0.02 ΔV_β = 1.83 +/- 0.02	ΔV_α = 1.65 +/- 0.02 ΔV_β = 1.72 +/- 0.02
30→60	0	0	120	300	ΔV_α = 3.48 +/- 0.13 ΔV_β = 3.53 +/- 0.09	ΔV_α = 1.12 +/- 0.02 ΔV_β = 1.22 +/- 0.03	ΔV_α = 6.58 +/- 0.02 ΔV_β = 6.71 +/- 0.05
30→60	+25%	+25%	325	700	ΔV_α = 9.50 +/- 0.49 ΔV_β = 9.47 +/- 0.44	ΔV_α = 2.82 +/- 0.12 ΔV_β = 3.23 +/- 0.10	ΔV_α = 3.69 +/- 0.10 ΔV_β = 3.55 +/- 0.08
30→60	-25%	-25%	325	700	ΔV_α = 9.59 +/- 0.31 ΔV_β = 9.07 +/- 0.33	ΔV_α = 3.98 +/- 0.16 ΔV_β = 3.89 +/- 0.10	ΔV_α = 8.09 +/- 0.18 ΔV_β = 8.31 +/- 0.23

verification has been performed with 95% confidence level and as a consequence UPPAAL has determined that 30 simulation runs are necessary. The verification of a single query (for the estimation of one value) lasted less than an hour. Additionally, an extended simulation was performed for six sample queries (one configuration) to check whether enough samples had been taken and the values had converged. The verification lasted 40 hours, but the obtained results were pretty similar and did not exceed in the worst case 5% of value difference.

As expected, load changes had the highest effect on the linear controller reference tracking performance with more than 10% voltage error during transients, on the contrary, it was not affected by parameter mismatch. What was interesting to observe was how the other two controllers performed in comparison to the linear controller. Under nominal conditions, both FS-MPC and NN controllers had three times lower errors in the reference tracking. The results showed that parameter mismatch, where the values in the system were smaller than the training data used, significantly deteriorated the NN controller's performance but not the FS-MPC controller. It was also observed for the value of V_{dc}, which does not vary in the training data, that the reference tracking error was over 10% of the reference voltage value.

V. CONCLUSION

In this paper, a robustness verification approach for comparing different controllers has been presented. The verification has shown in which conditions certain controllers were underperforming and will require parameter re-tuning or in the case of NN network which operating condition data needs to be added to the training. The same approach can likewise be applied to compare the controller performance in other PES applications and it is not limited only to stochastic loads. Grid conditions such as voltage dips, and harmonic pollution can also be included as other stochastic factors influencing the performance and robustness.

Future development of the proposed approach will focus on incorporating stability validation in an automated SMC test to find a set of controller parameters that can provide a stable response of PES with stochastic elements that are difficult to model in conventional simulation software.

ACKNOWLEDGMENT

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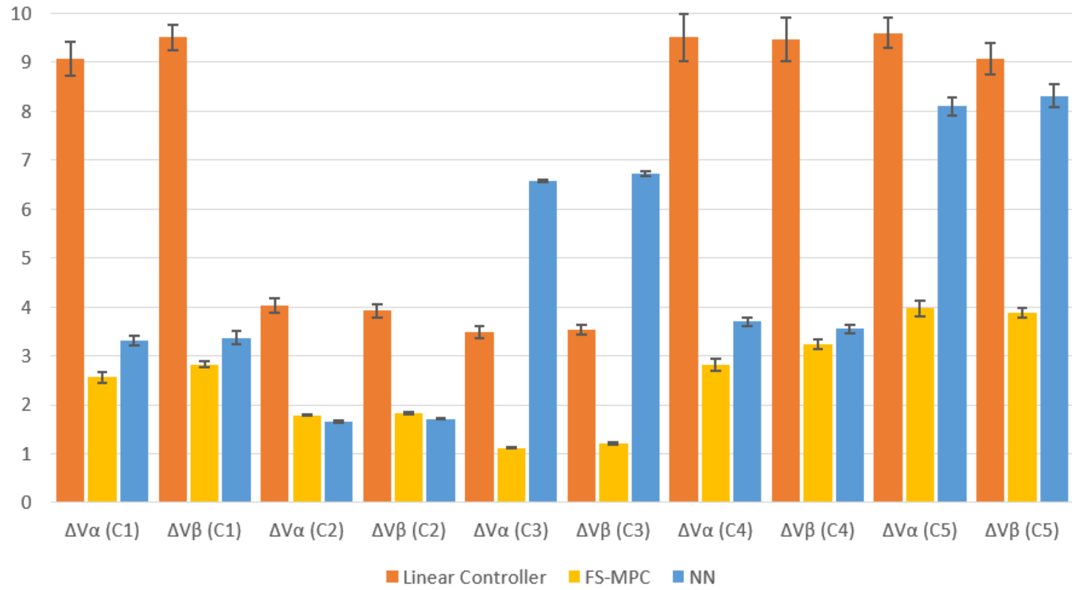

Fig. 10. Results for estimation of max RMSD (v_c) for three controllers with variable load 30→60Ω (nominal conditions and with parameter mismatch). Configurations:
C1: L error = 0, C error = 0, Vref ampl. = 325 V, Vdc = 700 V;
C2: L error = 0, C error = 0, Vref ampl. = 120 V, Vdc = 700 V;
C3: L error = 0, C error = 0, Vref ampl. = 120 V, Vdc = 300 V;
C4: L error +25%, C error +25%, Vref ampl. = 325 V, Vdc = 700 V;
C5: L error -25%, C error -25%, Vref ampl. = 325 V, Vdc = 700 V.

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