



# Effect of Social Distancing for Office Landscape on the Ergonomic Illumination

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**Abstract:** In office buildings valuable energy is wasted if not properly regulated as a function of presence of humans and active demands for illumination levels. Effective and clever usage of the sunlight is essential for optimal use of energy resources in large office buildings. Additionally, productivity of the employees can be improved by maintaining a constant light intensity. In context of social distancing enforced onto landscape area structure and occupancy, they have effects in the illumination pattern and ergonomics. This paper presents the practical setup to mimic the illumination regulatory problem in landscape offices and the dynamic properties of such a system in the context of social distancing regulations. The light level control is performed with distributed predictive control, whereas a comparison is made among various situations. The original contribution of the paper is a fast, adaptive control algorithm, which can deal with changing context parameters; e.g. varying landscape office structures.

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**Keywords:** social distancing, ergonomics, landscape office, distributed control, energy saving, multi-objective optimization.

## 1. INTRODUCTION

An enormous pressure is being exerted on policy makers for a climate-friendly and energy efficient society. Among the leading European countries for green energy policy, an important objective for Belgium is to reduce carbon monoxide and dioxide emissions while there is still a certainty of sufficient energy supply at an affordable price. About 70 % of Belgian electricity generation originates from nuclear energy (IEA, 2019). The current policy is closing all the nuclear power plants between 2022 and 2025. As pandemic outbreaks have negative economic and societal impacts, this affects energy production, in turn affecting long-term policy. As such, the energy grid with intelligent control of in- and out-take energy balance is second largest cyber-physical and human system, after supply chain manufacturing systems.

\* This work was supported by Ghent University special research fund MIMOPREC, STG020-18, Flanders Make-CONACON project nr HBC.2018.0235, and National Secretariat of Higher Education, Science, Technology and Innovation of Ecuador (SENESCYT)

Standard lighting in office buildings consumes a significant amount of electrical energy (Lee et al., 2018; Juchem et al., 2018). A reduction in energy consumption through improved lighting systems in office buildings has a major impact on the energy-driven objectives overall. A digitally based reduction in energy consumption is achieved by implementing a control strategy in the lighting systems by using smart lamps with omnipresence sensors detecting human presence and movement, along with geographical and weather dependent settings for daylight source seasonal variations. Due to the omnidirectional character of light and the interaction between the lights and the sensors, the ability to dim the lamps leads to a further decrease in energy consumption with improved light quality. Such control strategies already exist by using a feedback loop and various forms of ProportionalIntegralDerivative (PID) controllers (De Keyser and Ionescu, 2010; Juchem et al., 2019).

A major problem challenging the performance of the classical PID-controller is dealing with the coupling between the different inputs and outputs (MIMO-system). Consequently, controllers may start to oppose each others

actions. Recent emerging concepts from fractional calculus have been used to design fractional order PID controllers for this system and indicate their superior performance to classical control (Juchem et al., 2019). Hardware co-design has been already shown to influence the optimal performance in systems with strong interaction (Haemers et al., 2019), which motivates us to look at the effect of office landscape structure on some qualitative parameters. Advanced control strategies are employed to deal with such complex systems. Distributed predictive control is a good candidate for this class of processes, and parameterized versions offer efficient computational times (Faroni et al., 2017).

The emphasis of this paper is on the distributed control of the lighting setup as a function of landscape office structure in terms of controlled light zones to ensure social distancing at work and properly maximize the office occupancy in this safety limiting context. Firstly, a brief description of the test setup system and its experimentally identified model is provided. Next, a distributed model based predictive controller with multi-objective optimization algorithm is applied in its classical form, and also in its fast execution mode. Their ability to follow a pre-defined reference trajectory is investigated and presented here as a function of changing office landscape. Computational times to adapt to new structure and illumination ergonomics are evaluated. Finally, some conclusions and future steps in this research are given in the last section.

## 2. PROOF OF CONCEPT BENCHMARK SETUP

A laboratory benchmark setup representing an office floor is used for testing, as in figure 1, inspired by the example given in Quijano et al. (2017). It consists of a box containing eight lamps at the top and eight light sensors at the bottom, electronics, a real-time control unit (dSPACE™DS1104) and a DC voltage source. The light bulbs are type LAMP, INCANDESCENT MINI BAYONET/BA9S, 6.3V and the light sensors are light dependent resistors (LDR) type NSL 19M51.

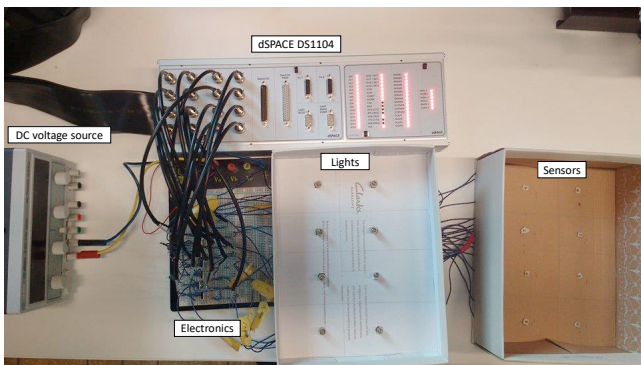


Fig. 1. A top view of the test setup that represents an office floor. Includes 8 lamps, 8 sensors, a DC-voltage source, a controller and associated electronics. The structure can be changed by adding/changing separating walls and their height among the controlled illumination zones.

The box is subdivided in eight zones. Each zone has a lamp and a sensor. As in actual office landscapes not all

zones are equally sized, some asymmetry was chosen in the size of the rooms. As light spreads omni-directionally, all light sources in the office will influence the readings of all sensors. In landscape offices, these may be with/out separating walls. The coupling effect between the different zones is affected by the presence or absence thereof, and the height of the separating walls. Disturbances due to incident sunlight through a window can be simulated by two additional lamps, installed in arbitrary places. The lamp inputs and sensor outputs are calibrated such that the controller can alter the input between [0,5] V in order to send a voltage between [5,10] V to the lights. The sensor voltage then varies between [0,5] V. Since the same lamps and sensors are used for each zone, the same characteristics apply.

## 3. SYSTEM IDENTIFICATION FOR CONTROL

The aforementioned setup is a Multiple-Input Multiple-Output (MIMO) system with (up to) eight inputs and eight outputs. Moreover, it has a very high degree of coupling between the different subsystems, making this a relevant control study object. The light system is represented as a Hammerstein system: the system is modeled as a sequence of a non-linear static system  $f(u(t))$  and a linear dynamic model  $P(s)$ . The linear dynamic model consists of two parts: the first part describing purely the dynamics  $P_d(s)$ , and the second part to describe the gain  $K_{ij}$ . To identify these different blocks, we rely on two experiments: a PRBS-response and a staircase experiment. For each lamp the response on each sensor is measured for both experiments. The relation between the input and the output of this model is described as follows:

$$y_i(s) = \sum_{i=1}^8 L\{f(u_i(t))\}(s) \cdot P(s)K_{ij} \quad (1)$$

with  $y_j$  the output of sensor  $j$ ,  $L\{\cdot\}(s)$  the Laplace transform and  $u_i$  the input to zone  $i$ .

The coupling matrix  $\mathbf{K}_{ij} \in \mathbb{R}^{8 \times 8}$  is determined from the staircase experiment from figure 2, and normalized with relation to the first zone (see an example of such normalized characteristics in figure 3). We assume a unit process gain. The staircase experiment initially described in (De Keyser and Ionescu, 2010) can be used to determine the function  $f(u(t))$ :

$$f(u_i) = \frac{y_j}{K_{ij}} \quad (2)$$

where  $u_i$  and  $y_j$  are the steady state gain values of the staircase test. A polynomial is used to model the function. The coupling matrix with the interaction coefficients  $K_{ij}$  belonging to light bulb  $i$  and light sensor  $j$ , for the case with walls is given by:

$$\mathbf{K}_{ij} = \begin{bmatrix} 1.19 & 0.34 & 0.11 & 0.06 & 0.63 & 0.25 & 0.11 & 0.05 \\ 0.86 & 1.11 & 0.43 & 0.15 & 0.49 & 0.60 & 0.26 & 0.10 \\ 0.18 & 0.45 & 1.15 & 0.53 & 0.12 & 0.24 & 0.67 & 0.29 \\ 0.08 & 0.12 & 0.52 & 1.34 & 0.06 & 0.08 & 0.29 & 0.78 \\ 0.31 & 0.16 & 0.09 & 0.07 & 1.18 & 0.51 & 0.14 & 0.07 \\ 0.23 & 0.24 & 0.18 & 0.11 & 0.70 & 1.11 & 0.77 & 0.13 \\ 0.12 & 0.19 & 0.32 & 0.24 & 0.13 & 0.37 & 1.08 & 0.40 \\ 0.06 & 0.08 & 0.22 & 0.43 & 0.06 & 0.12 & 0.51 & 1.19 \end{bmatrix}$$

The non-linearity seems to be negligible and a first order polynomial is fitted on the static characteristic to define

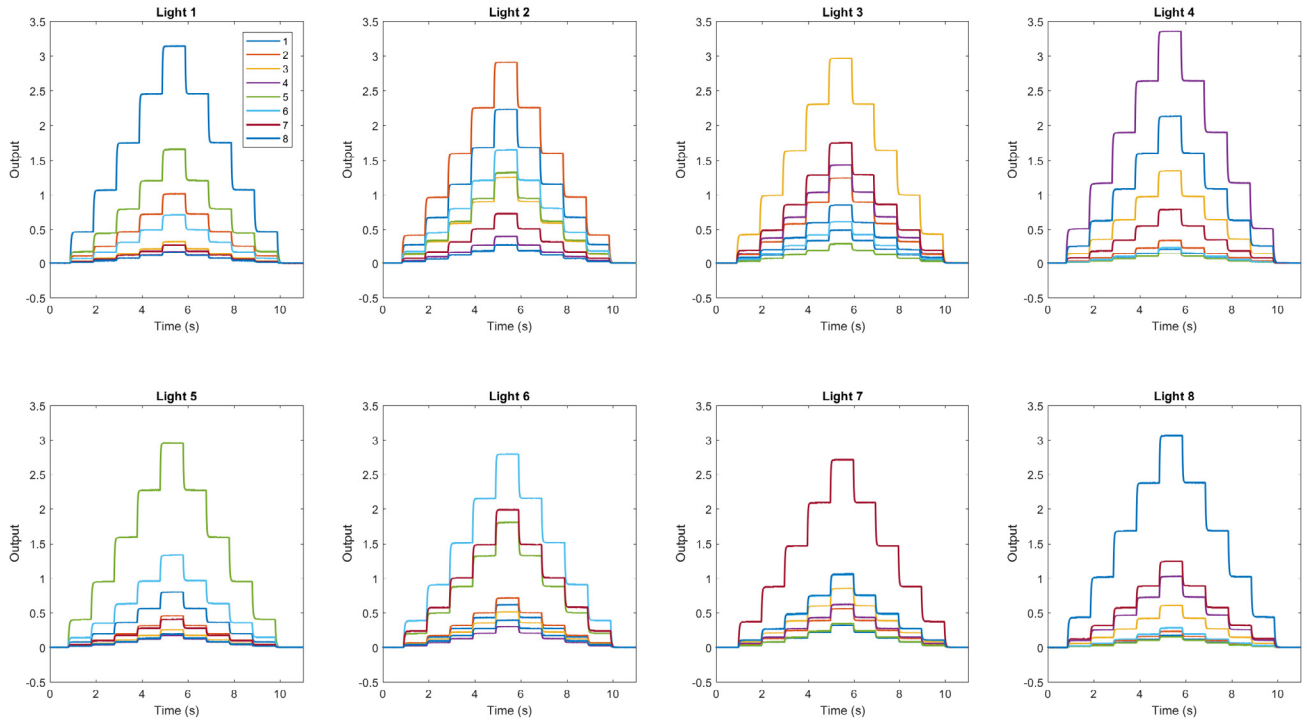


Fig. 2. Example of staircase experiment data for a case with separating walls.

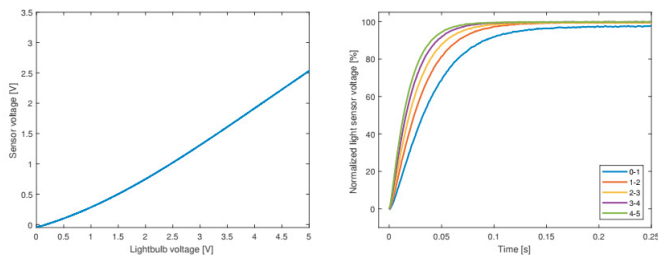


Fig. 3. Left: static characteristic after calibration; Right: normalized steps from staircase test after calibration.

an approximation function for the non-linear static gain. The obtained first order polynomial:

$$f(u_i) = 0.5334u_i - 0.2388 \quad (3)$$

The prediction error method based on a PRBS signal excitatory input has been used to identify a first-order model with 95% accuracy (not much noise on data due to data filtering). The dynamical model for the setup is given by

$$P(s) = \frac{33.33}{s + 32.50} \quad (4)$$

to which a gain matrix is coupled to provide the inter-zone dependency. An example of validation of the model for zone 1 is given in figure 4.

#### 4. PRIORITIZED MULTI-OBJECTIVE OPTIMIZATION FOR DISTRIBUTED PREDICTIVE CONTROL

The concept of Distributed Model Predictive Control (DiMPC) is shown in figure 5, and presented in (Maxim

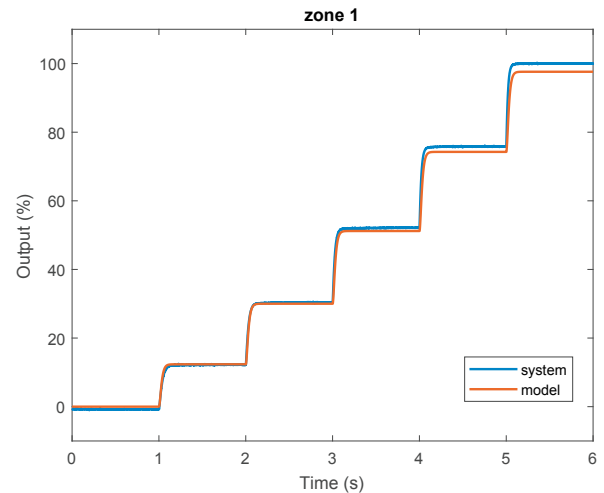


Fig. 4. Example of model validation.

et al., 2018), for the predictive control methodology of Extended Prediction Self-Adaptive Control (EPSAC) (Fernandez et al., 2019). A hands-on tuning of the predictive controller has been used as given in (Ionescu and Copot, 2019). Once the office structure is chosen, each subsystem has a local controller. This controller calculates the optimal solution for its own subsystem, for the reference signal  $w$ , but having the information from the other subsystems - iterative distributed control. This method has been shown to work well in large scale cyber physical systems with

human decisions in the loop (Fu et al., 2019). The iterative DiMPC structure consists of five steps:

**Step 1:** Subsystem  $i$  receives an optimal local control action  $\delta U_i$  at the iterative time as  $iter = 0$  according to the EPSAC, and the local control action  $\delta U_i$  can be rewritten as  $\delta U_i^{iter}$ , where  $\delta U_i$  indicates the vector of the optimizing future control actions with length of  $N_{ci}$ .

**Step 2:** The  $\delta U_j^{iter}$  ( $j \in N_i$ ) is communicated to the subsystem  $i$ , and the  $\delta U_i^{iter+1}$  is calculated again with the  $\delta U_j^{iter}$  from the other subsystems.

**Step 3:** If the termination conditions  $\|\delta U_i^{iter+1} - \delta U_i^{iter}\| \leq \varepsilon_i \vee iter + 1 > \bar{iter}$  are reached, the  $U_i^{iter+1}$  is adopted, where  $\varepsilon_i$  is the positive value and  $\bar{iter}$  indicates the upper bound of the number of iterations. Otherwise, the  $iter$  is set as  $iter = iter + 1$ , and return to **Step 2**.

**Step 4:** Calculate the optimal control effort as  $U_t = U_{base} + \delta U^{iter}$ , and the control effort is applied to the system.

**Step 5:** Set  $t = t + 1$  and return to **Step 1**.

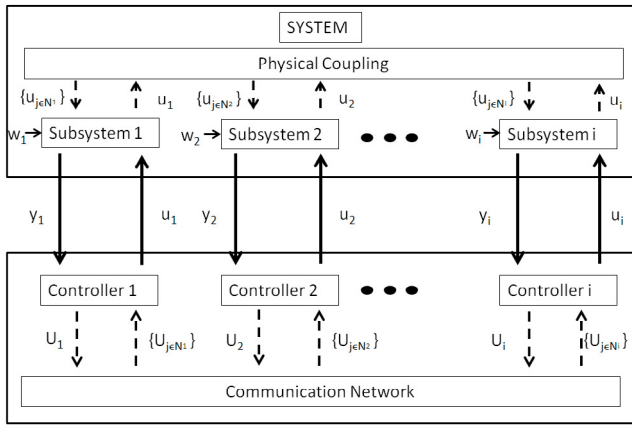


Fig. 5. Concept for iterative distributed model based predictive control.

The multi-objective optimization algorithm with priority settings from (Ionescu et al., 2019). The core value is that objectives are not relevant at all times, i.e. some have higher priority over others. For instance, one would first want to obtain a stable feasible solution at all times, followed by performance (minimizing error), followed possibly by energy cost penalties in the control effort. Other scenarios may be employed, where multi-objectives are evaluated at different time scales throughout the system operation (Ionescu et al., 2019). For example, the user comfort may be evaluated at a daily rate, whereas performance of light level is evaluated every sampling period of the controller. Ergonomics can be evaluated at monthly intervals based on human productivity under given illumination conditions. Economic costs on energy price may be then evaluated on monthly or yearly basis as part of the multi-objective optimization algorithm.

For fast interacting systems the main goal in terms of implementation efficiency is to reduce the computational time necessary within each sampling period. The proposed multi-objective distributed control (MODiMPC) has a structure that consists of several layers executed in order of priority. An example with three layers: safety, tracking performance and energy consumption is given in figure 6.

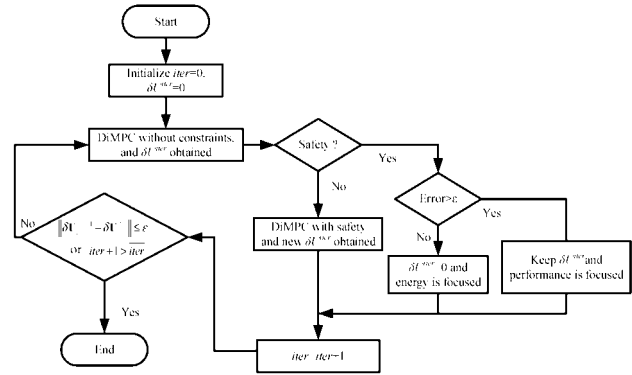


Fig. 6. Flowchart of the multi-objective DiMPC.

At startup we use null initial conditions. Analytical form of optimal control effort is calculated for the unconstrained solution. The optimal solution is the one that has the minimal tracking error. If the predicted inputs or outputs are not of the safety zone bounds, these constraints are included in order to ensure safety of the system. When this safety test is passed, the tracking error will be the next decision variable. If the tracking error is larger than the tolerance error ( $Error > \varepsilon$ ) then the focus will be on performance and the control effort will stay at  $\delta U_i^{iter}$ . If the tracking error is within the tolerance error ( $Error < \varepsilon$ ) then the focus is on energy and the control is kept  $\delta U_i^{iter} = 0$ . The same end conditions ( $\|\delta U_i^{iter+1} - \delta U_i^{iter}\| \leq \varepsilon_i \vee iter + 1 > \bar{iter}$ ) are applied as in the original DiMPC.

Finally, adaptation is included in the iterative mechanism as the interaction gains can be evaluated at interval times. When structure is changed, a calibration test is performed as the staircase experiment and delivers the interaction gains as in previous section. Structural changes which are unknown a priori can be detected by monitoring techniques in performance, such as those given in (Maxim et al., 2017). When a change in the context is detected (in this case office landscape structure), the calibration can be triggered and interaction matrix updated. This matrix is then used to adapt the gains of the local controllers.

## 5. RESULTS AND DISCUSSION

The results consist of both simulation and experimental testing of DiMPC algorithms, in basic version and fast version implementation. We investigate effects as a function of three configurations of the office landscape as a result of social distancing measures, as depicted in figure 7. The configuration 4/4 depicts two zones each with one person occupancy; configuration 3/3/2 depicts three zones with two person occupancy in areas with 3 lamps with a copier/printer area in the third zone with 2 lamps only. Finally, the configuration 2/2/2/2 depicts 4 zones with one person occupancy each, e.g. kitchen table for lunch break or coffee break occupancy.

A closed loop distributed MPC with performance optimization is illustrated in figure 8 as a comparison between the experimental test and simulated test. An excellent agreement is observed, which is a good indication on the quality of the system model and control algorithm.

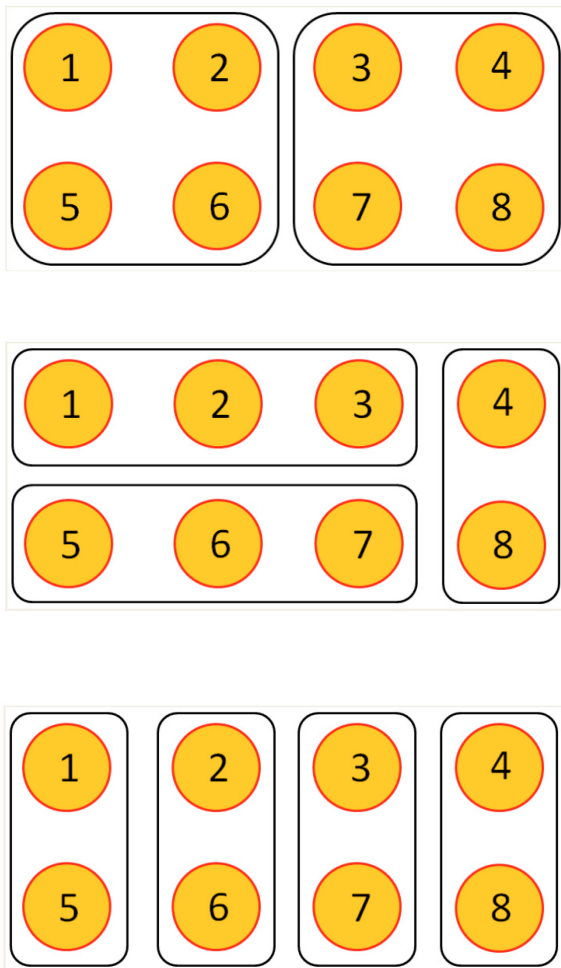


Fig. 7. Three landscape office configurations tested in this study, whereas 1-8 denote the lamp number and rectangle areas denote controlled zones: top 4/4 (2 zones), middle 3/3/2 (3 zones) and bottom 2/2/2/2 (4 zones).

The different office structures have influence upon the CPU time in DiMPC due to interaction among zones and number of controller variables. Figure 9 indicates the MODiMPC is faster in terms of computational times. The performance of DiMPC was dependent to different landscape office configurations, while the MODiMPC established no significant differences in performance among the various configurations. The maximum number of iterations necessary for convergence to solution in the optimization depends also on the configuration, with 10 iterations for 4/4, 6 iterations for 3/3/2 and 4 iterations for 2/2/2/2 structure.

Next, we examine the objective with respect to ergonomics (O-lowest, 5-highest eye comfort) and energy saving (in percent) potential among the various configurations with respect to reference configuration 4/4. Notice that despite the various usage of the office area, the reference values in the setpoints were not modified throughout tests (e.g. lower light might be set in kitchen, coffee or printer area,

etc.). The results with MODiMPC are summarized in Table 1.

Table 1. CPU time, iterations, ergonomics (0-100%) and energy saving (0-100%) with respect to reference configuration 4/4.

Area	CPU time (s)	Iter	Ergo (0-5)	Energy (%)
3/3/2	0.0453	6	4.48	38
2/2/2/2	0.0441	4	4.54	18

## 6. CONCLUSION

This paper illustrates the dependency of area configuration as a function of social distancing measures is simulation and experimental benchmark test setup. A fast optimization method is used with distributed predictive control and evaluated in terms of CPU time, number of iterations to converge within sample for optimal solution, ergonomics (illumination comfort as a function of structure) and energy saving potential (as a function of structure). Three structures are assumed to depict office desk areas, printer area, coffee room / kitchen area. The results indicate strong dependency between the choice of the system configuration and qualitative evaluation.

Other evaluations are currently ongoing, by modifying the setpoint (illumination) level in the controlled areas dependent on area functionality, changing interaction among zones as a function of delineating wall height, presence/absence of daylight, effect of disturbances (clouds or periodic shadowing from windmill blades, etc).

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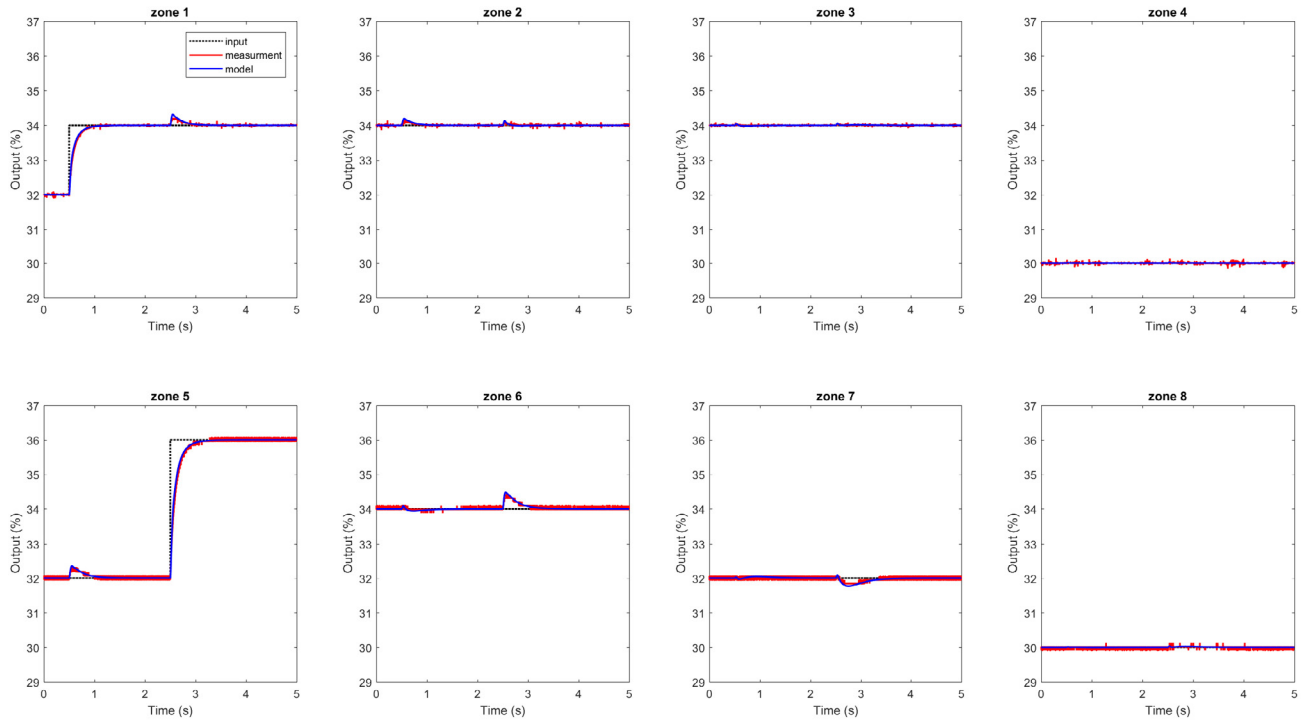


Fig. 8. Comparison of simulator and experimental setup for closed loop distributed MPC with performance optimization for the 4/4 landscape office structure. The high similarity was maintained for the other configurations as well, not shown here for lack of space.

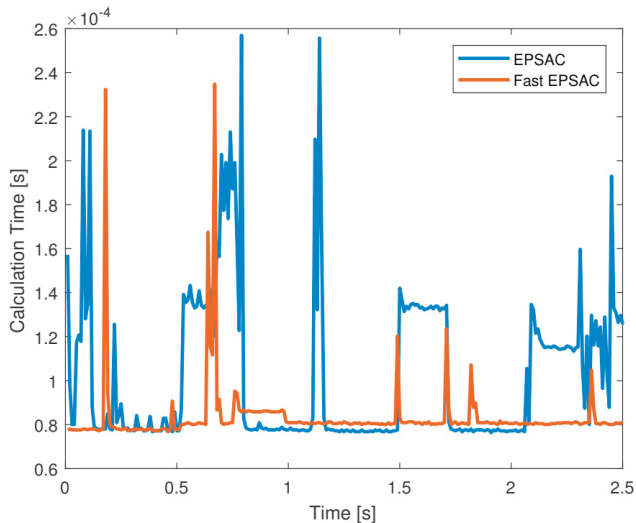


Fig. 9. Comparison in computational time of classical DiMPC EPSAC and its prioritized optimization case (Fast EPSAC).

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