A Deep Cognitive Venetian Blinds System for Automatic Estimation of Slat Orientation

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A deep Cognitive Venetian Blinds System for automatic estimation of slat orientation

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Abstract *Introduction.* Shading devices are used to control solar radiations that penetrate into the occupied environment through the windows with the aim of ensuring visual comfort and saving the building's energy consumption. Venetian blinds are commonly employed for the practicality and ease of application. However, occupants often do not change slat orientation causing unnecessary consumption and discomfort. Hence, automatic shading control systems can enhance the energy performance and make the environment more comfortable. *Method.* In this context, a cognitive venetian blinds system, denoted to as *CogVBS* and based on a deep feed-forward neural network, is proposed for automatic estimation of slat angle. Here, the EnergyPlus software is employed to simulate the test environment. *Results.* Experimental results demonstrate the promising performance of the proposed deep *CogVBS*, reporting a Root Mean Square Error (*RMSE*) and correlation coefficient (r) of 0.1018±0.0015 and 0.9319±0.0020, respectively. *Conclusion.* The achieved outcomes encourage the use of the proposed cognitive system in realistic environments.

Keywords Deep neural networks, Cognitive systems, Venetian blinds, Slat angle prediction

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1 Introduction

In the recent years, energy efficiency of buildings has gained a great deal of interest. Solar radiations introduced through the windows are indeed used as important source able to decrease the energy consumption of edifices [21], [19]. However, in order to determine the effect of a window on the energy consumption, several variables should be considered such as its size, orientation and climatic conditions [1], [15]. Daylight can result in a reduction of the heating load in the winter season and an increase of the cooling load in the summer [9]. In addition, an inappropriate amount of direct solar radiation may cause a sense of discomfort to the occupants with the consequent consumption of electric energy. External or internal shields (shutters, venetian blinds, curtains) are commonly used to filter the solar radiation penetrating into the environment [13], [3]. The shielding systems allow the occupants to regulate the incoming radiation. However, users typically adjust the blinds for improving visual quality with an increase of energy consumption. Identifying the best conditions to adjust solar shading and ensure energy savings is indeed a difficult task for the occupants [11]. Venetian blinds are widely employed as shading devices to control the inside comfort conditions of buildings. Standard blind systems are manually set by occupants but, it was noted that blinds are not usually re-adjusted until the occupants feel uncomfortable due to the sunlight [23]. Paik et al. [24] carried out an on-site study about the employment of blinds in offices and observed that blinds were mostly kept in a fixed position. Hence, in order to optimize the energy efficiency of the buildings as well as the comfort of occupants, automated blind control systems were proposed [17]. For example, Guillemin et al. [12] developed a genetic algorithm based shading control system capable of adapting the blinds considering the preferences of the occupants. In [26], Zhang et al. designed an open-loop control using the geometric properties of the window and an analytic solar angle model. The proposed control system was able to avoid direct penetration of sun rays from the room entrance. In [6] Chan et al. took into account daylight utilization and glare protection for implementing four control approaches, i.e., a sunlight redirecting control, a cut-off angle control, two control strategies to contrast glare able to achieve very good glare protection. Karlsen et al. [16] proposed a realistic solar shading control algorithm based on a combined logic of external and internal shading, used for office buildings in cold conditions; whereas, the control strategy proposed in [5] was able to move the lamellae only to fixed inclinations. Other approaches are based on the cut-off angle to prevent any glare effect on undesired secondary reflection [18] [2], [8]. It is worth mentioning that most of the existing approaches are based on specific parameters (such as position, reflection coefficient, inclination angle of the slats) or improved internal environment conditions without taking into account the presence of occupants. There is a limited number of studies that focused on the optimal slat angle of blinds by using not only the outdoor weather conditions but also the internal factors i.e., the presence of occupants in the environment. This is due to the difficulty to estimate the future state of the control system using rule-based strategies. In addition, such strategies are not adaptable to buildings with different external and internal conditions. In order to overcome the above limitations, cognitive systems based on artificial intelligence techniques have been developed to estimate efficiently the blinds' slat angle. In this context, a few number of works are presented in the literature. Hu et al. [14] proposed a system denoted as Illuminance-based Slat Angle Selection based on a series of shallow feed-forward neural network (FNN) able to forecast the illuminance levels and the optimal slat angles, achieving percentage errors less than 10% and 5%, respectively. Yeon et al. [25] developed a shallow FNN-based automatic blind control system for slat angle prediction with the aim to reduce cooling, heating, and lighting loads; while, recently, Luo et al. developed shading controller systems using surrogate models based on the radial basis function NN [22]. However, the aforementioned systems are based on shallow neural models. In contrast, here, deep architectures are taken into account. Specifically, a cognitive venetian blinds system, referred to *CogVBS* and based on deep FNN, is proposed for the prediction of the slat angle control estimated according to the control logic proposed in [23]. The developed *CogVBS* is trained using data generated by EnergyPlus, a widely simulation software employed to emulate shading models by considering physical phenomena associated to the energy of the building [7], [10], [4], [20]. The rest of the paper is organized as follows. Section 2 introduces the simulation environment carried out with EnergyPlus software. Section 3 describes the proposed methodology, including the evaluation of the slat angle, data pre-processing, the developed cognitive venetian blinds system and definitions of the performance metrics used. Section 4 reports the achieved results and Section 5 concludes the paper.

2 Simulation Environment

In this study, EnergyPlus is used as simulation software since it is able to deal with solar radiation and solar shading issues. The energy simulations are conducted dynamically, in order to take into account any capacitive effect present in homes. The test building consists of a square room of 25 m^2 with four walls oriented exactly in correspondence with the four cardinal directions i.e., South, East, West, North. Fig. 1 shows the representation of the test building located in the city of Cosenza, Italy (Latitude: 39.31 N; Longitude: 16.25 W) and also all the possible positions that the sun can assume during the year for this city. Each vertical surface includes a window with a size corresponding to 15% of the entire wall. Furthermore, the vertical walls, floor and roof have thermal transmittances equal to 0.38, 0.34 and 0.27 W/m^2K, respectively. The windows are composed of double glass and air gap (4-12-4) with a thermal transmittance of 1.91 W/m^2K. The sky model is simulated using an anisotropic radiance distribution of the sky ("CIE sunny clear day") with also a direct solar lighting. The presence of the occupants in the room is set randomly, alternating phases of presence and absence. LED lights are used as artificial lighting system with a linear control to provide an average illuminance of 500 Lux. An air conditioning system with fan coil powered by a heat pump is also included in order to maintain the indoor air temperature between 20 °C and 26 °C. Overall, the following parameters have been considered and used as input to the proposed cognitive network: presence of occupants (v_1), internal temperature (v_2), solar radiations incident on the vertical surface of each facade (South (v_3), North (v_4), East (v_5), West (v_6)), artificial light (v_7), and day light (v_8). The measures have been simulated for one year for a total of 525.592 samples (around 43.500 measurements per month). Each variable values ranged as follows: v_1 [0-1]; v_2 [12-34] °C, v_3

[0-690] W/m^2; v_4 [0-576]; v_5 [0-528] W/m^2; v_6 [0-1750] W/m^2; v_7 [0-0.1] kW; v_8 [0-13581] lux.

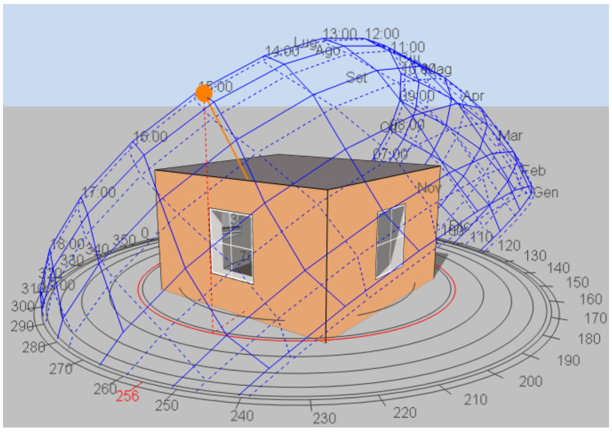

Fig. 1 Representation of the simulation environment with relative sun trajectories.

3 Methodology

3.1 Evaluation of slat angle

The slats angle inclination is estimated according to the logic proposed in [23]. This is defined in Fig. 2, as the angle between the vertical and slat plane. Note that, in this study, the southern surface of the building is considered. In order to determine the optimal inclination, three different cases are taken into account: winter operating conditions (if the internal temperature is lower than 21 °C), summer operating conditions (if the internal temperature is higher than 25 °C), intermediate conditions (if the internal temperature is ranged between 21 °C and 25 °C). In winter conditions, in case of no occupants in the room, the maximum solar radiation is introduced into the environment. If the sun is not visible from the window, this condition is obtained through an inclination of 110°; else, the angle sets the slats parallel to the direction of the sun rays as shown in Fig. 2 (left). This working mode is represented by the following equation:

$$slat = 90^\circ + \arctan\left(\frac{tan(\alpha)}{cos(\gamma - \gamma_w)}\right) \tag{1}$$

where α is the solar altitude (i.e., the angle between the direction of the sun rays and the horizontal plane); $\gamma - \gamma_w$ is the difference between the sun and surface Azimuth. Note that, if the slat value achieved by (1) is greater than 155° and the solar radiation incident on the window under analysis is less than 300 W/m^2, then the energy contribution of solar rays will be low and the angle is estimated by:

$$slat = 120^\circ - 0.66\alpha \tag{2}$$

In case of the presence of occupants in the room, it is necessary to arrange the slats in order to block the spokes, as shown in Fig. 2 (right). This working mode is represented by the following equation:

$$slat = 2\arctan\left(\frac{\frac{tan(\alpha)}{cos(\gamma-\gamma_w)} + \sqrt{[\frac{tan(\alpha)}{cos(\gamma-\gamma_w)}]^2 + 1 - (\frac{d}{L})^2}}{1 + \frac{d}{L}}\right) \tag{3}$$

where d is the slat distance and L is the slat depth. Here, d= 18.8 mm and L= 25 mm. In summer conditions, in case of no occupants in the room, in order to minimize the sun radiation, the angle of inclination is set equal to 180°. This corresponds to venetian blind completely closed. In case of occupants in the room, instead, the angle of inclination is 45°. In this scenario the venetian blinds are slightly opened to ensure a minimum of natural lighting. Finally, in intermediate operating conditions, the inclination is set to 80°. It is worth mentioning that in case of exposure to direct sun radiation the inclination is obtained by eq. (3) to prevent occupants from glare.

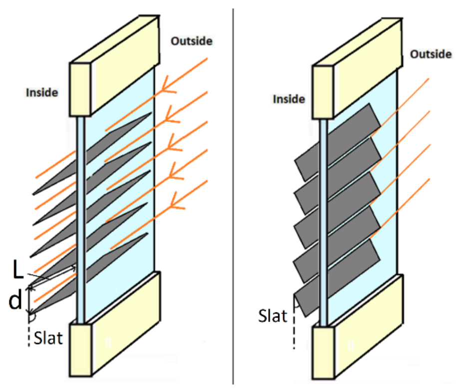

Fig. 2 Representation of the lamellae parallel to the direction of the sun rays (left). Minimum inclination of the lamellae able to block the sun rays (right).

3.2 Data pre-processing

In order to map data into the range [0-1], the min-max normalization techniques is used, according to:

$$\tilde{x} = \frac{x - min(x)}{max(x) - min(x)} \tag{4}$$

where max(x) and min(x) denote the maximum and minimum values of the x^{th} feature under analysis; while, $\tilde{x}$ is the normalized feature value ranging between [0–1].

3.3 Cognitive venetian blinds system

The cognitive venetian blind system is based on computational artificial intelligence techniques. Specifically, shallow and deep FNN are tested. Details are reported as follows.

3.3.1 Cognitive Architecture

The proposed deep network is composed of one input layer that includes the eight control parameters defined in Section 2, six hidden layers (with 100, 80, 60, 40, 20, 10 units, respectively) and one output neuron for estimating the slat angle control of the South facade. As the slat angle ranges between 0° and 180° (both conditions correspond to venetian blind completely closed), the output angle of the network was constrained to this range because values exceeding such limits are not physically applicable by the slat control system. Values exceeding 180 degree were set at 180°, and values below 0° were set at zero. The deep FNN was designed in MATLAB R2021b and trained in a supervised learning fashion for $2*10^2$ iterations, until the convergence of the loss function. It is worth mentioning that the proposed cognitive architecture and the training parameters were chosen according to a *trial and error* approach. In particular, the sigmoid activation function was set for all hidden units, while the linear transfer function for the output neuron. Furthermore, the mean square error was employed as loss function using the scaled conjugate gradient algorithm with the following optimized parameters: min-gradient: 10^{-6}, μ=0.005 (Marquardt adjustment parameter); σ= $5\text{x}10^{-5}$ (parameter for determining the change in weight for second derivative approximation); λ=$5\text{x}10^{-7}$ (parameter for regulating the indefiniteness of the Hessian). Table 1 reports different shallow and deep configurations tested by changing the number of hidden layers and neurons.

3.4 Performance metrics

The performance of the proposed cognitive venetian blind system is measured using the Root Mean Square Error ($RMSE$) and the correlation coefficient (r), defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i}^{N}(\tilde{y_i} - y_i)^2} \tag{5}$$

where N is the number of samples, $\tilde{y}$ and y represent the measured and target slat angle, respectively.

$$r = \frac{N\sum_i^N \tilde{y_i}y_i - \sum_i^N y_i \sum_i^N \tilde{y_i}}{\sqrt{[N\sum_i^N y_i^2 - (\sum_i^N y_i)^2][N\sum_i^N \tilde{y_i}^2 - (\sum_i^N \tilde{y_i})^2]}} \tag{6}$$

with r ranged between [-1;1] (r=0 denotes no correlation; whereas, r =-1 and r =1 indicate perfect negative and positive correlation between the target and the estimated value).

Furthermore, the behaviour of the building is evaluated according to the energy consumption of the air conditioning system and according to daylight. The latter represents the illuminance from the solar source alone, received on a plane 0.8 m above the ground in the center of the room. The Usefull Daylight Illuminance (UDI) parameter is defined as the percentage of time in which illuminance falls within a range of values that is considered comfortable by the users. In the present analysis the range 200-800 lux was considered.

4 Experimental results

Table 1 reports comparative prediction performance in terms of $RMSE$ and r coefficients. It is worth mentioning that in order to determine the best cognitive configuration, shallow and deep FNN with different number of hidden units and layers were tested. Furthermore, in order to estimate the efficiency and generalization capability of the proposed cognitive venetian blinds systems, the k-fold cross validation technique (with k=10) was employed. Hence, the achieved outcomes are reported as average values ± standard deviation. Experimental results show that the highest performance were achieved by the cognitive systems composed of deeper models such as $CogVBS_{4-7}$ and $CogVBS_{10,11}$. In particular, best results were achieved by $CogVBS_6$ with $RMSE$ of 0.1018±0.0015 and r coefficient of 0.9319±0.0020. In contrast, as can be seen in Table 1, shallow models achieved low prediction results. For example, $CogVBS_1$ (with only 1-hidden layer) and $CogVBS_{22}$ (with only 2-hidden layers) reported $RMSE$ of 0.1250±0.0112; and, r coefficient of 0.8943±0.0213. Table 1 reports also the

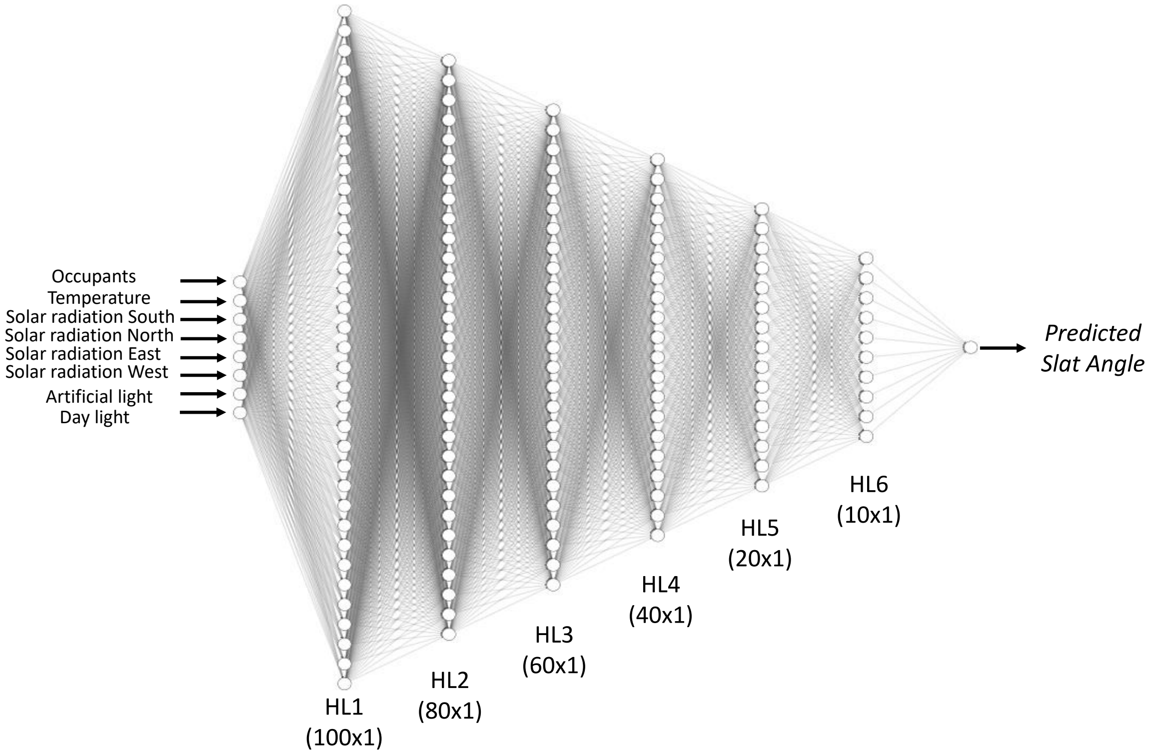

Fig. 3 Architecture of the proposed deep Cognitive Venetian Blinds System ($CogVBS$).

Time Computing (TC) and Memory Computing (MC) for training the different prediction networks. The experiments were conducted on a high performance workstation with graphics processing units (Intel UHD graphics 630 and NVIDIA GeForce RTX 2080 Ti) of 43 GB. As can be observed, smaller models were more performing in terms of TC and MC (e.g., $CogVBS_{21}$: TC=5.35 s, MC=2%), but with lower results; vice-versa, larger models were less performing in terms of TC and MC (e.g., $CogVBS_7$: TC=82 s, MC=11%) but with higher results. However, it is worth noting that, although the proposed deep models were time and memory consuming, they took approximately only 80 s with a memory usage of only 10%. Fig. 4 reports the average $RMSE$ and correlation coefficient r along with the standard deviation (i.e., vertical lines) of all the developed cognitive venetian blind systems. It is to be noted that the $CogVBS_{4-7}$ and $CogVBS_{10,11}$ achieved comparable results. However, $CogVBS_6$ reported less standard deviation in terms of $RMSE$ and r parameters, making this configuration more stable and reliable. As an example, Fig. 5 show comparisons between the desired slat angle (green) and the predicted values (red) estimated by deep cognitive models $CogVBS_{6,7,10,11}$. As can be seen, the cognitive systems were able to provide very good prediction performance. In contrast, Fig. 6 shows the behavior of shallow networks $CogVBS_{1,12,21,22}$. The estimated values by the models were indeed not able to follow effectively the desired angles. In addition, in order to validate statistically the achieved results, the correlation between the target slat angle and the angle estimated by $CogVBS$ was evaluated by Pearson's linear correlation test. A positive and significant correlation ($p < 0.05$) could be observed for every network. In particular, the highest correlation coefficient ($r \approx 0.93$) were achieved by $CogVBS_4$,$CogVBS_5$, $CogVBS_6$, $CogVBS_7$, $CogVBS_{10}$ and $CogVBS_{11}$. Finally, an energy efficiency analysis was carried out over a sample period in the year. In particular, in a sample week in the month of August, a cooling energy consumption of 38.3 kWh was observed, with a 12% saving compared to rule-based logic. Visual comfort was also adequate as the UDI200-800 index is 85% while it is 70% with the rule-based logic.

5 Discussion and Conclusion

In the present research, a deep cognitive venetian blinds system, denoted as $CogVBS$ was developed in order to predict the slat angle achieved by the rule-based control-logic proposed in [23]. To the best of our knowledge this is the first work using a deep architecture for predicting the slat orientation of venetian blinds. Specifically, a custom deep FNN composed of six-hidden

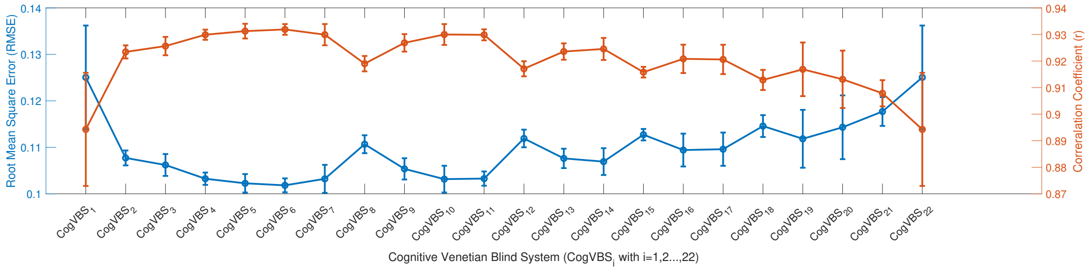

Fig. 4 Root Mean Square Error ($RMSE$) and correlation coefficient (r) estimated for all the developed cognitive models. Dot points denote the average values, whereas, vertical lines denote the standard deviations.

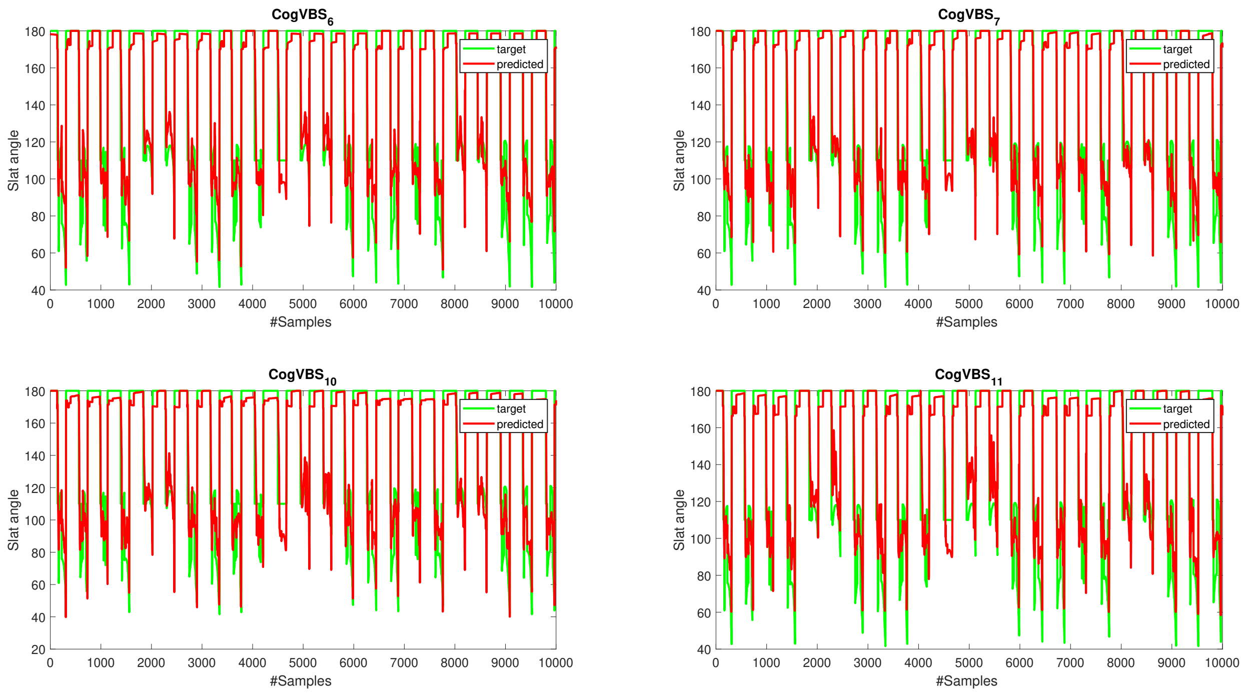

Fig. 5 Comparison between the desired slat angle (green) and the predicted values (red) estimated by the cognitive models ($CogVBS_{6,7,10,11}$) that achieved high performance.

layers of 100, 80, 60, 40, 20 and 10 hidden neurons ($CogVBS_6$) was developed to receive as input the eight control parameters taken into account (Section 2) and output the predicted orientation of blinds installed in the South facade. The EnergyPlus software was employed to simulate the test building composed of a room with a window for each exposure. Although the network was designed to predict slats angles belonging to the venetian blinds of the South facade, solar radiations incident over the four faces of the building were included since affect the internal temperature. Experimental results showed that the proposed deep cognitive model, achieved very good performance in terms of $RMSE$ and r coefficient: 0.1018±0.0015 and 0.9319±0.0020, respectively. It is to be noted that other deep networks achieved good results (e.g, $CogVBS_{4,5,7}$ and $CogVBS_{10,11}$), but with greater standard deviation. It is worth mentioning, as can be noted in Fig. 5 that the slat angle estimated by CogVBS varies gradually over time, in contrast to the slat angle estimated by the model which, at the exact time of sunset, automatically closes the venetian blinds completely (slat angle = 180) regardless of possible residual natural light. The natural lighting is instead taken into account by the neural model which learns to estimate the optimal angle on the basis of a plurality of input factors. In other words, the model learns that in the presence of daylight the blinds should not be completely closed, which the analytical model is not able to take into account. Hence, the proposed CogVBS estimates the angle using the detected illu-

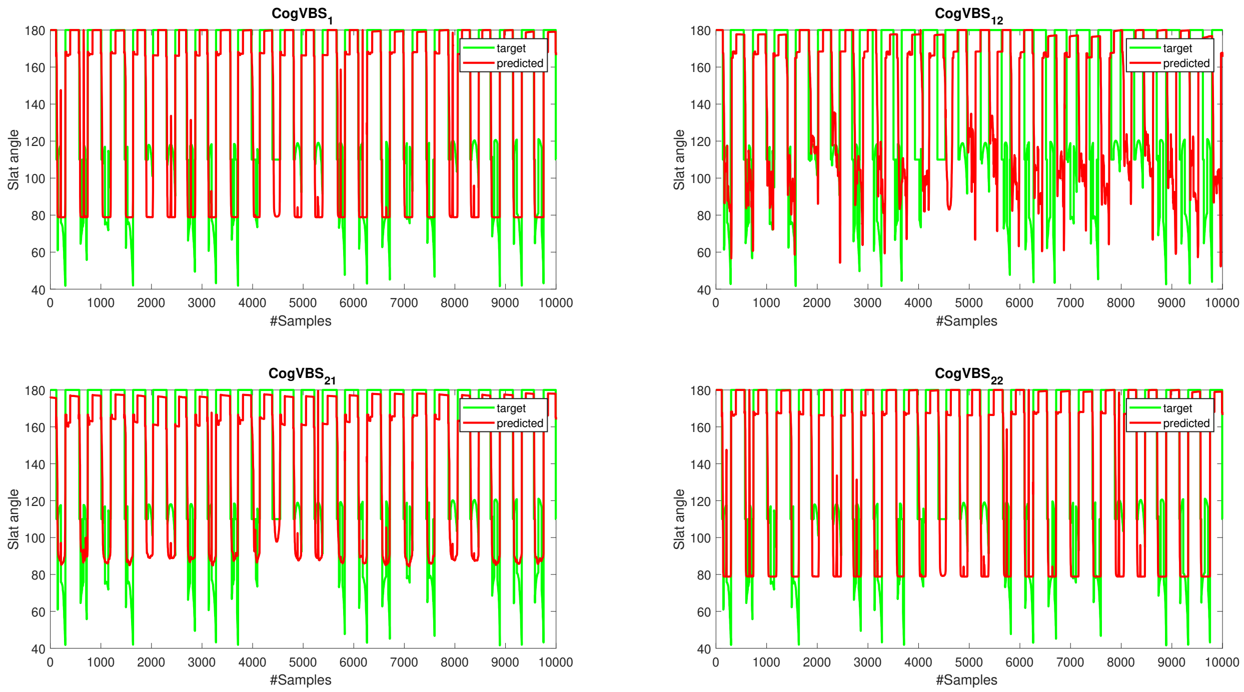

Fig. 6 Comparison between the desired slat angle (green) and the predicted values (red) estimated by cognitive models ($CogVBS_{1,12,21,22}$) that exhibited poor performance.

minance and solar radiation data with no information about the position of the sun in the sky. In this way, the sun may be down, but if an adequate natural illuminance is still present, the network will not close the blinds instantly, as the analytical model would do, and will adapt to the context. In this perspective, the neural model reproduces the analytical model but overcomes its limitation of the on-off logic linked to the time of sunset. As consequent the visual comfort of the occupants improves since that are able to benefit from the sunlight for a longer time. It is also to be noted that the rule-based algorithm reported in [23] depends on several operating variables (e.g., geometry of the window, internal and external environmental conditions, etc) and should be reinvented when new parameters are considered. The cognitive strategy overcomes this drawback as it is easily adaptable to different contexts, also when new variables are included. To this end, a long term campaign of data acquisition will be carried out in the future on a set of sample buildings. It is worth mentioning that data should be collected from sensors for different slat angle settings and used as input to the neural system to be developed. The energy consumption of the building should be then evaluated for different slat angles and different input variable settings. In the end, for every input variable setting, the slat angle ensuring optimal energy consumption could be identified and used as target response to train a neural system. Such a data collection campaign would be time consuming but it would allow, for the definition of a neural system taking into account, many input variables while ensuring the best energy consumption, which is nowadays a urgent problem to be solved both for economic and environment reasons. In addition, we intend to investigate the prediction performance also for the North, West and East facades of the simulated building. Moreover, a more complex building with multiple rooms, levels and other control parameters will be also taken into account. Finally, the proposed system will be implemented in a real test-bed as part of the COGITO project. This set up will provide the opportunity to evaluate the performance of the proposed system in a operational environment.

Compliance with ethical standards

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- **Conflict of interest** The authors declare that they have no conflict of interest.
- **Data availability statement** The dataset analysed during the current study is available from the corresponding author on reasonable request.
- **Ethical Approval** This article does not contain any studies with human participants or animals performed by any of the authors.
- **Informed consent** Not Applicable - No consent was needed to carry out this research.

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Table 1 Performance (i.e. Root Mean Square Error ($RMSE$) and correlation coefficient (r)) of the developed cognitive venetian blinds systems composed of shallow and deep FNN with different hidden layers (HL), one input layer that includes eight input parameters and one output neuron. Results are expressed as average score ± standard deviation. Time computing (TC) and memory computing (MC) are also reported.

Model	**Input**	**HL1**	**HL2**	**HL3**	**HL4**	**HL5**	**HL6**	**HL7**	**Output**	*RMSE*	*r*	*Time Computing [s]*	*Memory Computing [%]*
$CogVBS_1$	8	100	-	-	-	-	-	-	1	0.1250±0.0112	0.8943±0.0213	15.83	5%
$CogVBS_2$	8	100	80	-	-	-	-	-	1	0.1077±0.0016	0.9234±0.0025	37.07	8%
$CogVBS_3$	8	100	80	60	-	-	-	-	1	0.1062±0.0024	0.9256±0.0035	62.05	9%
$CogVBS_4$	8	100	80	60	40	-	-	-	1	0.1033±0.0019	0.9299±0.0025	70.06	10%
$CogVBS_5$	8	100	80	60	40	20	-	-	1	0.1023±0.0020	0.9313±0.0028	79.03	10%
$CogVBS_6$	8	100	80	60	40	20	10	-	1	0.1018±0.0015	0.9319±0.0020	78.98	10%
$CogVBS_7$	8	100	80	60	40	20	10	5	1	0.1032±0.0030	0.9299±0.0040	81.89	11%
$CogVBS_8$	8	50	-	-	-	-	-	-	1	0.1107±0.0019	0.9190±0.0029	9.60	4%
$CogVBS_9$	8	50	30	-	-	-	-	-	1	0.1054±0.0023	0.9268±0.0033	16.88	5%
$CogVBS_{10}$	8	50	30	10	-	-	-	-	1	0.1032±0.0029	0.9300±0.0039	19.47	5%
$CogVBS_{11}$	8	50	30	10	5	-	-	-	1	0.1033±0.0018	0.9299±0.0021	23.95	5%
$CogVBS_{12}$	8	20	-	-	-	-	-	-	1	0.1119±0.0019	0.9171±0.0028	9.93	3%
$CogVBS_{13}$	8	20	10	-	-	-	-	-	1	0.1076±0.0021	0.9236±0.0031	11.09	3%
$CogVBS_{14}$	8	20	10	5	-	-	-	-	1	0.1069±0.0029	0.9245±0.0042	15.14	3%
$CogVBS_{15}$	8	10	-	-	-	-	-	-	1	0.1127±0.0012	0.9158±0.0020	5.65	3%
$CogVBS_{16}$	8	10	8	-	-	-	-	-	1	0.1094±0.0035	0.9208±0.0053	9.91	3%
$CogVBS_{17}$	8	10	8	5	-	-	-	-	1	0.1096±0.0036	0.9206±0.0055	13.75	3%
$CogVBS_{18}$	8	8		-	-	-	-	-	1	0.1146±0.0024	0.9129±0.0038	5.47	3%
$CogVBS_{19}$	8	8	4	-	-	-	-	-	1	0.1118±0.0062	0.9169±0.0101	9.43	3%
$CogVBS_{20}$	8	8	4	2	-	-	-	-	1	0.1143±0.0069	0.9131±0.0108	12.93	3%
$CogVBS_{21}$	8	4		-	-	-	-	-	1	0.1177±0.0031	0.9079±0.0049	5.35	2%
$CogVBS_{22}$	8	4	2	-	-	-	-	-	1	0.1250±0.0112	0.8943±0.0213	8.87	3%