Data-driven occupant-centric rules of automated shade adjustments: Luxembourg case study

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**Abstract.** This study presents key findings of observed datasets in a nearly zero-energy office building for over 66 working days from June to mid-September in 2019, Luxembourg. Measurements of indoor and outdoor environmental parameters as well as user-shade override adjustments were extracted from the KNX-based building management system (BMS) in 47 office rooms located in three typical floor levels. Relative frequency and “rate of change” of blind use were analysed in terms of window orientation, occupancy level, and the time of the day. Logistic regression and data mining techniques were used to identify potentially useful and understandable occupant behaviour patterns and reveal the main triggers behind blind adjustments. The well-designed automation system together with the inner glare protection formed the base of very low user-shade interactions. A mean of 0.184 manual blind adjustments per day per office. Eight regression sub-models were developed and all were incapable of predicting user-shade lowering and raising events. Alternatively, two user profiles were mined based on 20 rules gained from clustering analysis: user (β) was representing the passive user, and user (μ) the medium user. Overall, we conclude that the automated shading system in this building is satisfactory, user-friendly, and a robust control system.

1. **Introduction**

Occupant behaviour is proven to have a significant influence on energy consumption in buildings [1]. A possible solution to avoid discrepancies between predicted and real energy consumption due to occupants’ actions is the use of fully automated systems. For instance, automated shading systems represent a promising solution for improving indoor thermal and visual conditions as well as energy-saving for cooling. However, occupants frequently override or disable the automated shading systems either indicating discomfort or expressing their desire for a customized indoor environment or visual contact with the ambient. Based on field studies of monitoring occupants’ operations such as user-shade interactions, researchers may extract user behaviour patterns to improve understanding of occupant behaviour as well as user-centric design practices. Few studies [2, 3] were found to explore occupant-centric rules related to the automated shading systems in high-performance office buildings.

To this end, the purpose of the current study was to explore occupant-centric rules of automated shade adjustments and investigate the triggers behind the user interaction with shades. A better understanding of the logic and patterns of occupant behaviour can not only facilitate better predictions of the building performance but also support the role of user-centric design by considering the needs and preferences of the users while planning and design of the shading systems and their control.
2. Methodology

The preliminary patterns of user behaviour were analyzed in terms of the relative frequency and the rate of change of blind use. The rate of change was defined as the number of user-shade adjustments per day or office. Two statistical methods were used in the current study. First, logistic regression was applied to the given datasets to discover the associations between the physical measurements and user-shade interactions, and derive a model that predicts the likelihood of user-shade override adjustments. Second, clustering analysis and association rules mining (ARM) were used in the given dataset analysis to overcome the lack of personalization using regression analysis and allow more accurate assumptions on the group and complex behaviors. Both regression and clustering analysis were performed in SPSS software, while Rapid Minor - an open source data mining program - was used for ARM analysis.

3. Case study description

The new headquarter of Goblet Lavandier is a five-story office building located in Niederanven, Luxembourg. The building consists of a quadrilateral concrete structure (25×25 m) with a galvanized metal sheet façade (Figure 1). The core area of the building comprises circulation and sanitary units and creates a naturally daylit office zone. The workspaces are located along the building perimeter and were designed with the highest standards of a healthy and comfortable work environment [4].

3.1. Monitored offices and parameters

The characterization of occupant behaviour was performed in 47 offices over 66 working days. The offices are situated on three typical floor levels and occupied by an average of 2-6 workers per office. The majority of the offices are located along the quadrilateral perimeter facing one of the four cardinal directions (north, south, west, and east). The offices’ windows are designed to have the same height and width. Each window is equipped with a double shading system, an external automated shading system, and inner manual glare protection (Figure 2).

Monitored weather parameters included global irradiance \((I_{gl}) \text{ W/m}^2\), external vertical illuminance \((E_{out}) \text{ Lux}\), air temperature \((T_{out}) \text{ °C}\), solar azimuth, and altitude. The outdoor parameters were measured using a weather station mounted on the rooftop of the building. Indoor parameters included air temperature \((T_{in}) \text{ °C}\), relative humidity (RH), and \(\text{CO}_2\) concentration (ppm). The indoor parameters were measured with Netatmo data loggers distributed in 11 workspaces in the building. Shading system-triggered actions and user-triggered actions were recorded as event-based measurements. Whereas shading deployment degree was expressed in percentage terms. Only the blind position activated by the control system was detected (0%: fully open, 100%: fully closed). All given datasets were resampled every 5 minutes using an excel tool developed by Mr. Jurgen Leick from Goblet Lavadier. For the analysis purpose, the range of data was limited to working days between 6:00 am and 8:00 pm.

1 Source: Lucas Roth, https://www.golav.lu/.
2 Source: Jürgen MÜLLER, https://www.golav.lu/.

Figure 1. Perspective view of the building1.

Figure 2. The double shading system approach2.
3.2. Configuration of the automated shading system
The external shading system is operated automatically based on light and temperature thresholds. Occupants can adjust the external blind at any desired position using a switch button next to the office door. The system is fully lowered when global irradiance exceeded 250 W/m² on each façade with a horizontal slat position to maximize the view to the outside (0 min delay time). When the irradiance exceeded 400 W/m², the slat angle inclination was set up to 15° to keep a good incidence of daylight. Thresholds values would be increased for temporary cloud sky cover to assure leisurely blind movements. The high-quality performance of the shading control sensors was considered during the operation phase. Further research was done to examine the accuracy of light sensors.

4. Results and discussion
4.1. Frequency of observed user-shade override adjustments
A total number of 1148 blind changes were recorded over 66 working days in 47 offices. About half of the operations were triggered by the users. 274 user-shade lowering actions and 298 raising actions. Resulting in an average of 0.184 blind use per day and office.

Figure 3.a shows that the highest rate of user-shade adjustments was in the east elevation. An average of 3.93 adjustments per day has occurred. However, fewer interactions were observed in the west and north elevation comparing to the east and south facades. This can be explained that the east and south facades experienced the greatest variations in global irradiance. In figure 3.b, a higher frequency of user override adjustments was observed in shared offices comparing to single-occupancy and open-plan offices. However, occupants tend to be more reluctant to control their environment if others are present because of social constraints [5]. Figure 4 shows the relative frequency of user-shade override adjustments during the time of the day. We noticed that shades on the east and south were adjusted more
frequently by occupants in the morning rather than the rest of the day, while the opposite occurs for the shades of the west facades. Only for shades in the north facades, the users tend to raise the blinds in the evening the most frequently. This is similar to Inoue et al. [6] study findings.

In the majority of the cases, few user-shade adjustments occurred. This is due to (a) correct and acceptable automated shade control settings and high-quality performance of light sensors, and (b) additional inner glare protection which provides less effort to avoid visual discomfort. We analyzed the daily average profile of CO₂ levels in 9 offices in the building to estimate the occupancy presence. We found that approximately 97% of the study period, these offices were occupied. To conclude, that the low manipulation rate of the blind use was not related to the occupancy absence.

4.2. Regression analysis results

The following formula (1) represents the probability of user-shade actions as a function of several explanatory variables:

\[
\text{logit (likelihood of observing blind override)} = \beta_0 + \beta_1 (E_{out}) + \beta_2 (I_{gl}) + \beta_3 (T_{out}) + \beta_4 (\text{tan}_d) + \beta_5 (T_{in}) + \beta_6 (\text{Rh}) + \beta_7 (\text{presence (CO}_2\text{ concentration)}) + \beta_8 (\text{AOV}%\%) + \beta_9 (\theta_{\text{slat angle}}) + \beta_{10} (\text{time of the day})
\]

Where \(\text{tan}_d\): tan of solar profile angle, \(\theta\): Slat angle position (0, 60, 80 degrees), \(\beta_0\): the intercept and \(\beta_i\) variable coefficient.

The thermal and visual stimuli were identified by earlier research to influence blind use [7,8]. Separated analyses were made to predict the probability of user-shade override actions (lowering and raising) for each façade (E, S, N, W) inducing eight sub-models (M1-M8). The forward regression method was used to select the explanatory variables that have a statistically significant influence on the value of the dependent variable (p-value < 0.05). Table 1 indicates the logistic regression coefficients (\(\beta\)) for each predictor variable, and the performance test for each model (AIC and Nag. R squared

Table 1. Logistic regression coefficients and goodness-of-fit for the eight sub-models.

| Predictors      | M1_L_E | M2_R_E | M3_L_N | M4_R_N | M5_L_S | M6_R_S | M7_L_W | M8_R_W |
|-----------------|--------|--------|--------|--------|--------|--------|--------|--------|
| logit           | 0.249  | 0.225  | 0.231  | 0.233  | 0.231  | 0.225  | 0.231  | 0.225  |
| L_{gl}          | 2.8    | 2.34   | n.a.b  | 9.92   | n.a.b  | -2.28  | n.a.b  | n.a.b  |
| E_{out}         | n.a.b  | n.a.b  | n.a.b  | 2.34   | n.a.b  | 5.18   | n.a.b  | n.a.b  |
| T_{out}         | 2.94   | n.a.b  | 3.34   | n.a.b  | n.a.b  | -5.15  | n.a.b  | n.a.b  |
| tan_d           | n.a.b  | n.a.b  | n.a.b  | n.a.b  | n.a.b  | n.a.b  | n.a.b  | n.a.b  |
| RH              | n.a.b  | -1.50  | n.a.b  | n.a.b  | n.a.b  | 4.22   | -3.71  | n.a.b  |
| Presence (CO₂ level) | n.a.b | n.a.b  | n.a.b  | -4.86  | 3.52   | n.a.b  | 5.31   | n.a.b  |
| T_{in}          | n.a.b  | 1.90   | n.a.b  | n.a.b  | 4.20   | n.a.b  | 3.63   | n.a.b  |
| Time of the day (1) | 4.30  | 3.24   | ------ | 2.83   | ------ | n.a.b  | n.a.b  | n.a.b  |
| Time of the day (2) | 2.24  | 2.84   | ------ | 2.40   | ------ | n.a.b  | n.a.b  | n.a.b  |
| Time of the day (3) | 2.54  | 2.53   | 1.61   | 2.54   | 2.53   | 1.61   | 2.54   | 2.53   |
| AOV [%]         | n.a.b  | n.a.b  | n.a.b  | 1.22   | 1.79   | -0.90  | 2.25   | n.a.b  |
| Slat angle (0)  | 17.19  | 0.85   | 0.50   | 0.50   | 0.50   | 0.50   | 0.50   | 0.50   |
| Slat angle (60) | 16.66  | 0.50   | 0.50   | 0.50   | 0.50   | 0.50   | 0.50   | 0.50   |
| Constant        | -26.17 | -7.78  | -23.70 | -7.86  | -26.65 | -6.04  | -22.94 | -7.07  |
| AIC             | 1020.9 | 1053.4 | 315.92 | 723.14 | 529.2  | 672.71 | 421.08 | 256.95 |
| - 2 Log likelihood | 1010.9 | 1045.4 | 307.92 | 713.14 | 529.2  | 672.71 | 421.08 | 252.95 |
| Nag. R²         | 0.137  | 0.067  | 0.107  | 0.089  | 0.125  | 0.039  | 0.227  | 0.041  |
| Prediction success | 98.8% | 98.9%  | 99.7%  | 99.3%  | 99.4%  | 99.6%  | 99.8%  | 99.8%  |

Logit P = constant + ∑ Bi xi, n.a.b NOT ELECTED BY THE LOGISTIC REGRESSION
Overall, we conclude that the developed regression sub-models were all incapable of predicting user-shade actions, even if they are particularly accurate for “no action=0” (100% of prediction success). The limitation of the models could be due to the missing measurements of indoor illuminance during the study period, which represents one of the main triggers behind blind use [7].

4.3. Data mining analysis results
Data mining techniques such as cluster analysis and association rules were proposed as an alternative methodology to overcome the lack of personalization using regression statistical analysis. Data mining was defined as “The analysis of large observational data sets to find unsuspected relationships and to summarize the data in novel ways so that owners can fully understand and make use of the data” [9].

4.3.1. Cluster analysis of occupant behaviour patterns
First, interactivity patterns clustered occupant behavior based on the frequency of user-shade override adjustments per day. The following interactivity patterns were clustered using the K-means algorithm:
- Passive adjustments [C01]: 66% of offices assigned (range of 0-0.17 times per day).
- Neutral adjustments [C02]: 21% of offices assigned (range of 0.18-0.36 times per day).
- Active adjustments [C03]: 13% of offices assigned (range of 0.44-0.58 times per day).

Second, motivational patterns clustered the factors which derive the users to overrule the automated shading systems. The clusters were based on the impact factor (regression coefficients) of each variable that could influence the user-shade override actions. Accordingly, logistic regression was performed to define the most statistically significant variables in each office. About 25-30 of the building offices were considered in the analysis. The rest of the offices had the lowest frequency of user-shade adjustments. Three clusters of user-shade lowering and two clusters of user-shade raising were defined (Figure 5a &b).

- Shade lowering cluster 01 [C01_L]: 12% of offices assigned and associated to the time of the day (early morning and morning) and outdoor weather conditions (T_out, tan_d).
- Shade lowering cluster 02 [C02_L]: 24% of offices assigned and associated to the time of the day (early morning until the afternoon) more than physical parameters.
- Shade lowering cluster 03 [C03_L]: 64% of offices were assigned and appeared to be more influenced by slat angle position than physical and time-related drivers.
- Shade raising cluster 01 [C01_R]: 63 % of offices were assigned and appeared to be more influenced by the slat angle position and time of the day (noon and afternoon) than physical drivers.
- Shade raising cluster 02 [C01_R]: 37 % of offices assigned and associated to the time of the day and indoor air temperature.

4.3.2. Association rules mining results (ARM)
The frequent pattern growth algorithm (FP growth) was employed to mine the association rules. To obtain significant results from ARM analysis, support of 50%, the confidence of 50%, and a lift of 1,
were set as the minimum thresholds. Such criteria indicated that for each association rule mined at least 50 percent of all the data set contained premise and conclusion, with the probability that a specific premise leads to a specific conclusion was more than 50%. Such mining generated 20 rules which provide useful information for the study purposes. Based on the 20 rules mined, two possible working user profiles (user \( \beta \), user \( \mu \)) can be drawn in this study:

- User type (\( \beta \)) was representing the passive user who tended to overrule the automated shading systems on the average between 0.09–0.17 times per day (passive adjustments). User \( \beta \) was mainly influenced by the time of the day and the current blind state for both lowering and raising overrule adjustments.
- User type (\( \mu \)) was representing the medium user who tended to overrule the automated shading systems on the average between 0.18–0.36 times per day (neutral adjustments). User \( \mu \) was mainly influenced by the time of the day and the current blind state only for raising overrule adjustments.

5. Conclusions and future work

Based on the quantitative analysis of the given datasets in the current study, we conclude that the rate of change of user-shade override adjustments was relatively low compared to the findings of previous studies [1,2]. This is due to (a) correct and acceptable automated shade control settings and high-quality performance of light sensors, and (b) additional inner glare protection which provides less effort to avoid visual discomfort. The commonly used modeling approach “regression method” was not successful in explaining the occupant behavior in this case. Data mining techniques as alternative methodology suggest an improvement in exploring occupant patterns and allow more accurate assumptions of complex and diverse behaviour. A cross-sectional web-based survey was conducted in summer 2021 in the current case study to reveal subtle and non-physical drivers behind the user-shade adjustments and to justify the occupants’ acceptance and satisfaction of the automated shading system.

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References

[1] Wagner, A., O’Brien, W., & Dong, B. (2018). Exploring Occupant Behavior in Buildings. Wagner, A., O’Brien, W., Dong, B., Eds.
[2] Meerbeek, B., te Kulve, M., Gritti, T., Aarts, M., van Loenen, E., and Aarts, E. (2014). Building automation and perceived control: A field study on motorized exterior blinds in Dutch offices. Building and Environment, 79 (SEPTEMBER), 66–77.
[3] Reinhart, C. F., and Voss, K. (2003). Monitoring manual control of electric lighting and blinds.
[4] Markus L. (2018). Objektbericht Energiekonzept & Nachhaltigkeit_ Neues Bürogebäude von Goblet Lavandier & Associés.
[5] Brien, W. O., Kapsis, K., and Athienitis, A. K. (2013). Manually-operated window shade patterns in office buildings : A critical review. Building and Environment, 60, 319–338.
[6] Inoue, T., Kawase, T., Ibmoto, T., Takakusa, S., and Matsuo, Y. (1988). The development of an optimal control system for window shading devices based on investigations in office buildings, ASHRAE Trans. 94.
[7] Haldi, F., and Robinson, D. (2010). Journal of Building Performance Simulation Adaptive actions on shading devices in response to local visual stimuli. (October 2014), 37–41.
[8] Mahdavi, A., Mohammadi, A., Kabir, E., and Lambeva, L. (2008). Journal of Building Performance Simulation Occupants’ operation of lighting and shading systems in office buildings, (November 2014), 37–41
[9] Hand DJ., Mannila H., and Smyth P. (2001). Principles of data mining. MIT Press.