Sensitivity analysis of design parameters of envelope enclosure performance in the dry-hot and dry-cold areas

Pingan Ni¹, Wanjiang Wang¹,†, Hanjie Zheng², Wensi Ji¹

¹ College Architectural and Civil Engineering, Xinjiang University, Urumqi 830000, China
² MOE Key Laboratory of Deep Earth Science and Engineering, College of Architecture and Environment, Sichuan University, Chengdu 610065, China

Abstract

In a bid to quantify the sensitivity of envelope enclosure’s design parameters in the dry-hot and dry-cold areas and to provide a reference for the local building performance design, this paper uses ANN modelling which combined with the improved Garson algorithm to calculate the connection weight sensitivity (CWS), the first-order sensitivity (RBD-S1 and DMIM-S1) and the global sensitivity (DMIM-delta) of the design parameters. These parameters were calculated by using different methods in SALib. Through the verification and analysis of the sensitive result, the applicability of the CWS and DMIM-delta was confirmed. Among the design parameters involved in this study, the sum of the sensitive values of S-D, S-N and S-A exceeds 60% in each performance label, and the sum of the sensitive values of WWR_S and WWR_N exceeds 20%. The performance design of envelope enclosure in this area requires applying reasonable shading components and appropriate optimisation of the North and South of WWR. After the sensitivity analysis process, the calculation efficiency of the model can be improved as far as possible without reducing the accuracy of the model in the later simplified calculation and multi-objective optimisation. The building performance simulation model has a high degree of non-linearity, and the interpretability of the model can be enhanced through the sensitivity analysis process. Although the internal calculation process is unknowable, the perception of the results caused by the input parameters is significantly enhanced.

Keywords: Dry-hot and dry-cold areas; Envelope enclosure performance; Improved Garson algorithm; Global sensitivity

† Corresponding author.
Email address: 95543595@qq.com
Nomenclature

| Symbol | Meaning |
|--------|---------|
| S1     | First-order Sensitivity, which is local sensitivity |
| GSA    | Global Sensitivity Analysis |
| CWS    | Connection Weight Sensitivity |
| LHS    | Latin Hypercube Sampling |
| ANN    | Artificial Neural Network |
| BPM/BPPM | Building performance Model/Building Parametric Performance Model |
| CDD/HDD | Cooling/Heating Degree-Days (CDD/HDD) |
| SALib  | A Sensitivity Analysis Library in Python |
| RBD-FAST | Random Balance Designs - Fourier Amplitude Sensitivity Test |
| DMIM   | Delta Moment-Independent Measure |
| UDI    | Useful Daylight Index |
| sDA    | Spatial Daylight Autonomy |
| PMV    | Predicted Mean Vote |
| $R^2$  | Coefficient of Determination |
| MAE    | Mean absolute Error |
| MSE    | Mean Square Error |
| RMSE   | Root Mean Squared Error |
| Loss   | Loss function curve during ANN training |
| MOEA   | Multi-objective Evolutionary Algorithm |

1 Introduction

The progress of human society is reflected in the comprehensive optimisation of building performance, which is promoted by the joint efforts of architectural research and design practice. With the progress of scientific and technological civilisation, people’s necessities for visual and thermal comforts of the living environment are also improved accordingly. At present, the maintenance of building indoor environment comfort is still dependent on active energy supply, which makes the building energy consumption in the operation stage accounts for a large proportion of the global total energy consumption [1]. The building is like a complex machine that is easily affected by various parameters such as environment, materials, equipment, form and human behaviour. Therefore, the design of buildings with better performance is an important strategy to achieve sustainable development [2].

This study can provide more accurate results for the optimisation of envelope enclosure. However, most previous studies can only discuss samples under certain specific design situations due to the research’s complexity. With the further development of computer simulation technology, many building performance simulation tools (such as EnergyPlus, DeST, ESP-R, DOE2, TRNSYS and IES VE) have been applied in architectural research and design practice. In particular, the Ladybug Tools for building performance are maturing, providing researchers with a more flexible and diverse solution for building optimisation. Ladybug Tools can analyse EPW format files of building weather data and visualisation methods to perform some basic building performance simulations [3–5]. Honeybee (HB) uses visual programming to structure and input building morphological parameters and meteorological data to the computing engine (such as EnergyPlus, Radiance, Daysim and Thermal) to realise the construction of building performance simulation schemes and data conversion in the GH platform. Based on this, HB reads the numerical calculation results into GH for analysis and visualisation [6]. EnergyPlus (EP) [7, 8] is a building energy simulation engine developed by the Department of Energy (DOE) of the United States, which can simulate and analyse the overall energy consumption of heating, refrigeration, lighting, ventilation and other energy consumption of the building. Besides, HB realises the collaborative optimisation of indoor lighting and energy consumption through the coupling calculation of Radiance and EP [9, 10].

Sensitivity analysis (SA) is a method used to quantitatively describe the importance of model input variables
Sensitivity analysis through AAN modelling for buildings in China

to output results, which plays an essential role in understanding complex models [11–15]. Meanwhile, it can help to identify the influence of input parameters on the results, make model builders fully aware of the uncertain response caused by changes in model inputs and provide decision-makers with rich insights on management issues [16, 17]. The optimisation of building performance is a multi-objective optimisation problem under the comprehensive action of multiple parameters. In previous studies, Sanchez et al. [18] analysed and illustrated the potential use of integrating first-order and second-order sensitivity analyses into building energy models (ESP-R). Taking an apartment building as an example, the sensitivity analysis is carried out by using the principal effect method (Morris), including the analysis of the interaction between the input parameters (secondary analysis). To effectively perform the interval size of multi-level sensitivity analysis variables, nonlinear management and the availability of various outputs, Hughes et al. [19] used two global sensitivity analysis techniques, such as the necessary effect and the variance-based method, to determine the U value and demand temperature of SAP wall as the most critical uncertainty parameters so far. The U values of SAP roofs, windows and floors together explain 96% of the observed yield changes. Kulhanek and Poyraz [20] studied three different exterior wall (Clay) designs, which were convenient in suggesting the energy characteristics of passive house design in general. They proved the feasibility of using the dominant weight method to carry out a sensitivity analysis of envelope enclosure parts containing energy. Sun [21] made a systematic sensitivity analysis of large parameters in near-zero energy building (NZEB) and carefully selected more accurate design parameters (especially those with serious sensitivity effects), which is of great value to help designers to improve the design of the NZEB system. Maltais and Gosselin [22] conducted a sensitivity analysis based on daylight simulations of an office building in Montreal to identify the most influential architectural design variables on the 15 feature lists. Finally, it is concluded that the WWR and the overhang size are among the most influential parameters of AEL and AGI, while the direction and aspect ratio of the building and the visible light transmittance have relatively little influence.

In the recent study, Ostergard et al. [23] introduced a novel approach to explore multi-dimensional design spaces and guide multifactor decision-making in sustainable building design. Sensitivity metrics and metamodels show the combined effect of changing individual inputs and how to correct unnecessary output changes. The proposed approach has been developed and tested by using standard models to assess energy requirements, thermal comfort and lighting in real building cases. Al-Saadi and Al-Jabri [24] studied the optimal design of envelope enclosure under hot climate by using genetic algorithm (GA) technology and carried out life cycle cost (LCC) analysis with EP simulation programme. A sensitivity analysis was performed using a validated housing model to determine the upper and lower limits for optimising the search domain. The results show that the window shading is thermoresistant and economically viable in the selected climate. Depending on the energy cost, the insulation cost of an enclosure system in a hot climate will be 2.5-5 cm more than that of an enclosure system in a warm and humid climate. Liu et al. [25] built a simulation model through the energy consumption simulation analysis method and verified the reliability of the model by comparing it with the actual energy consumption. In order of energy-saving sensitivity, the thermal design parameters of six building envelopes, including the heat transfer coefficient of external walls, were analysed. According to the results of sensitivity analysis, suggestions for each factor are put forward. Delgarm et al. [26] studied the integration of factor-based OFAT and variance-based sensitivity analysis methods with EnergyPlus through MATLAB to define the main variables that affect building energy efficiency at the early stage of building design. It is proved that in the selected typical case studies, the window size is the main parameter for annual cooling, heating and total building energy consumption, while visible light transmittance of glass has little effect on annual lighting in the selected climate conditions.

According to the research of the existing literature, it is found that most of the previous research is the sensitivity analysis under the action of a single computing engine or method, and there is still a gap in the sensitivity analysis of multiple performance tags under the action of multi-parameters coupling. The improvement of this study is not only to evaluate the sensitivity analysis of space energy consumption, comfort and lighting performance under the action of multi-dimensional design parameters but also to use various sensitivity analysis
methods to evaluate the quantitative results obtained and ensure the applicability of the calculation method.

2 Materials and methods

Residential buildings in dry-hot and dry-cold climate zones were selected as the research object of this paper. Local buildings were investigated and operation data were obtained. Through simulation verification, the parameterised envelope performance evaluation model is reconstructed, while on this basis the simulated sample data are obtained, and the sensitivity analysis is carried out. The overall technical route is shown in Figure 1.

1. Build the energy consumption model of the original building, and obtain the simulated data of energy consumption through the simulation technology;
2. Fit the simulation data with the building operation data to verify the applicability of the simulation tool on the premise of ensuring accuracy;
3. By extracting the optimised performance design parameters, the parameterised performance coupling simulation model was reconstructed;
4. Latin hypercube sampling (LHS) was used to sample and save the combination table of design parameters;
5. Colibri plug-in in GH platform is used to automatically control the cycle solution and write out the calculation results;
6. ANN modelling was carried out between the sampled samples and the simulation results, and the accuracy of the model was verified;
7. Calculate the weight value of the neural network in the process of (6), and calculate CWS with the improved Garson algorithm;
8. RBD-S1 was calculated by using RBD-FAST in SALib;
9. DMIM-S1 and DMIM-delta were calculated by using the DMIM algorithm in SALib;
10. Various sensitivity indexes were verified and comprehensively analysed.

2.1 Overview of the research object

The area represented by the Turpan is located in the Cold B area of the China Building Thermal Design Division. The climatic condition of the area is characterised by abundant sunshine, rare rainfall, average annual precipitation <20 mm, >100 hot days higher than 35°C, extreme high temperature in summer up to 49.6°C and extreme minimum temperature in winter –28.7°C [27]. According to the CDD/HDD [28] calculation method provided by ASHARE, the CDD and HDD in this area are 579 and 2758, respectively. So it has the characteristics of dry-hot and dry-cold, which are alternating.

The New Energy Demonstration Zone of Turpan is the first large residential area in western China to fully utilise multi-energy complementarity, which is a high-quality object in terms of architectural design and energy utilisation. On the one hand, the residential buildings in this area are modern residential buildings, and the design techniques and materials adopted are quite different from the traditional local dwellings (Figure 2). And to adapt to the continuous evolution of the local climate and environment, traditional dwellings in Turpan generally use ‘thick walls’ and ‘small windows’ to sacrifice indoor lighting to improve the indoor thermal environment. Therefore, indoor lighting and vision are mighty imperfect, which need to put forward a reasonable improvement plan through the design intervention.

In addition, the heating and air conditioning in this area adopt solar-ground source heat pump technology, which is a multi-source complementary system in the right operating conditions. According to the field investigation and interview of the buildings in this area, most villagers are more acceptable to central heating, but there are also terrible operation cases. Because of its lack of independent control and high overall operating cost, some residents even give up the central heating system and choose to install an independent control system. Also, from the initial design scheme’s perspective, the shading system for the building’s exterior windows was
not implemented in the later construction process, which was also one of the problems that increased energy consumption and reduced comfort.

2.2 Create a parameterised performance model

Many design parameters affect building energy consumption. In this paper, based on the original design parameters, the original building energy consumption evaluation model is established (Figure 3). First, the simulation parameter settings were adjusted according to the original architectural design parameters (Table 1). The mean relative error between simulation data and operation data is calculated, and the result is 14.68%. Energy consumption during the life of a building is influenced by a complex set of factors, such as uncontrolled human factors and changes in meteorological conditions. Based on this, it can be concluded that the model has high accuracy. Parameters that can be used for design optimisation are extracted to construct the parameterised
building performance model (PBPM), which were set as adjustable intervals. Finally, the LHS [29–33] was used to generate design parameter combination samples (Table 2).

![Fig. 3 Original building energy consumption model.](image)

**Table 1** Building materials parameters for simulation.

| Property (opaque)       | Wall Insulation (W) | Floor Insulation (R) | Property (transparent) | Window |
|-------------------------|---------------------|----------------------|------------------------|--------|
| Roughness (opaque)      | Rough               | Rough                | Rough                  | Thickness (m) |
| Thickness (m)           | 0.20                | 0.12                 | –                      | 0.08   |
| Conductivity (W/m*K)    | 1.74                | 1.74                 | 0.03                   | 2.4    |
| Density (kg/m³)         | 2,500               | 38                   | 2,500                  | 38     |
| Specific heat (KJ/(kg*K)) | 1.010             | 1.010                | 1.010                  | 0.7    |
| Roughness (optics)      | 0.1                 | 0.1                  | 0.1                    | 0.02   |
| Reflection coefficient (ρ) | 0.4               | –                    | 0.3                    | 0.78   |

1. Property (opaque): non-transparent material property; Property (transparent): transparent material property.
2. Insulation layer (W): external wall insulation; insulation layer (R): external roof insulation.

**Table 2** Parameters value ranges and sampling.

| Name of parameter                  | Shorthand | Value range | Samples |
|------------------------------------|-----------|-------------|---------|
| Window-to-wall ratio in north      | WWR_N     | 0.15–0.7    |         |
| Window-to-wall ratio in south      | WWR_S     | 0.15–0.7    |         |
| Window-to-wall ratio in west       | WWR_W     | 0.15–0.7    |         |
| Window-to-wall ratio in east       | WWR_E     | 0.15–0.7    |         |
| Window heat transfer coefficient   | WHTC      | 0.8–2.8     | 3,000   |
| Wall insulation                    | WI        | 0.05–0.12   |         |
| Roof insulation                    | RI        | 0.06–0.15   |         |
| Depth of shading                   | S-D       | 0.1–1.2     |         |
| Numbers of shading                 | S-N       | 1–10        |         |
| Angle of shading                   | S-A       | –60–60      |         |

In this paper, literature research is carried out through commonly used building parameters. In most cases, the main differences of the modern residential building envelope in different climate zones of China are the control of the building, the size of the window, the thermal performance of the envelope and whether to take corresponding shading measures. In terms of parameter variable selection, the window-wall area ratio (WWR_N,
WWR_S, WWR_W and WWR_E), wall insulation layer thickness (WI), roof insulation layer thickness (RI) and comprehensive heat transfer coefficient of external windows (WHTC) are mainly selected in each orientation according to the local residential building design and construction feasibility. Due to the various forms of shading systems outside the building, this paper selects stationary blinds as the test objects. The depth (S-D), numbers (S-N) and angle (S-A) of the shading components on the exterior windows of the building were selected. LHS sampled a total of 10 envelope performance design parameters that could be optimised in the design stage.

In terms of the selection of performance labels, lighting energy consumption and heating energy consumption may be increased under the effect of improving heat insulation and shading in summer. Therefore, main energy consumption labels, such as the heating load of the building, the cooling load of air conditioning and lighting load that meets the requirement of illumination, are selected. By extracting the whole space’s relevant values, the PMV calculation module in EP is adopted to calculate the spatial PMV values of the corresponding samples.

The remaining simulated parameters are not taken as the main discussion object, and the original design is selected because of its small impact on the research. UDI and sDA [34] values were calculated through the coupling of Radiance and DaySim, which were used as an essential basis for evaluating the lighting quality of building space. Because the two labels’ data changed in the same direction and had a high correlation, UDI and sDA were merged into a comprehensive spatial lighting evaluation label DWS [Eq. (1)].

$$DWS = \frac{1}{2} (UDI - sDA)$$

2.3 Sensitivity analysis methods

2.3.1 Sensitivity analysis based on ANN

According to the existing research, artificial neural network (ANN) [35–37] has been applied in various industries to solve the related problems of pattern recognition and prediction. ANN can build models with predictive ability according to the characteristics of existing operational data. However, due to the inherent uncertainty (black box) in the model constructed by the researchers, the understanding and optimisation of the model are greatly troubled. To solve the black box effect of ANN, many researchers have made outstanding contributions in this aspect: Garson [38] proposed the Garson algorithm in 1991; Olden and Jackson proposed the randomisation test in 2002 and Muriel Gevery proposed the PaD2 method in 2005 [39]. This paper uses Python to code an improved Garson algorithm [Eq. (2)] [39], while CWS values are calculated based on the
high precision of $R^2$ [Eq. (3)], MAE [Eq. (4)] and RMSE [Eq. (5)] of ANN regression model evaluation indexes. In addition, MSE [Eq. (6)] is adopted as the Loss function of the training process in this paper, so the optimal Loss value of the ANN model can also be used as the performance evaluation index of the model.

$$Q_{ij} = \frac{\sum_{j=1}^{L} \left( \frac{|w_{ij}v_{jk}|}{\sum_{i=1}^{N} |w_{ij}|} \right)}{\sum_{i=1}^{N} \sum_{j=1}^{L} \left( \frac{|w_{ij}v_{jk}|}{\sum_{i=1}^{N} |w_{ij}|} \right)}$$  \hspace{1cm} (2)

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (\bar{y}_i - y_i)^2}$$  \hspace{1cm} (3)

$$MAE = \frac{1}{m} \sum_{i=1}^{m} |(y_i - \hat{y}_i)|$$  \hspace{1cm} (4)

$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2}$$  \hspace{1cm} (5)

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2$$  \hspace{1cm} (6)

### 2.3.2 Toolset of sensitivity analysis

With the popularity of parameter sensitivity analysis in research and practice in various industries, the tools available for parameter sensitivity analysis have also been developed. Among them, the SA analysis modules in Simlab software and R software are more commonly used. Besides, a sensitivity analysis library, SALib [40,41], based on Python programming language, has also attracted researchers’ attention. It can select different sampling methods according to specific problems and provide more comprehensive sensitivity analysis methods (such as Sobol, Morris, FAST and DMIM). SALib provides a separate workflow, which means it is not directly linked to mathematical or computational models. Besides Sobol and Morris methods, RBD-FAST [40–42] and DMIM [42,43] are representative first-order sensitivity and global sensitivity analysis methods in SALib, which make the sensitivity analysis of given sample data possible. RBD-FAST is an improvement on FAST [42, 43], which aims to make sensitivity analysis easier than any other available methods and significantly reduce the computational cost of the analysis. The main development idea of DMIM, combined with the methods proposed by Borgonovo and Plischke, can simultaneously evaluate the first-order sensitivity (DMIM-S1) and the global sensitivity (DMIM-delta). Because the calculation process of RDB-FAST and DMIM is relatively complicated, and there are some application examples in SALib, this paper will not introduce the calculation method in detail.

### 3 Results of sensitivity analysis

#### 3.1 Evaluation of ANN-BPM

To ensure the effectiveness of the model established by ANN, the accuracy of the data modelling used in this paper is evaluated. The ANN established in this paper adopts a three-layer full-link structure (one input layer, one hidden layer and one output layer) and adopts MSE as the loss function. In the ANN training process, 10-fold cross-validation [44,45] is used to prevent over-fitting of the model, and the best model is selected to calculate the sensitivity index. The loss curve of the model (Figure 5) is drawn, which can be seen that the model reaches the best accuracy around 235 times of running, with the value of $R^2$ is 0.91, the value of RMSE is 0.31 and MAE is 0.18 (Table 3) meeting the standard of a high-precision regression model.
3.2 Verification of sensitivity analysis methods

The design parameters of the performance models discussed in this paper may influence each other and relate to each other in terms of performance labels. The results of sensitivity analysis are better verified to understand the characteristics and applicability of each calculation method. The sensitivity indexes obtained by different methods were verified (Figure 6). There was little difference between RDB-S1 and DMIM-S1, so the two methods can verify each other to predict the reliability of the DMIM-delta (Table 3). And there are some differences between CWS and the other three sensitivity indexes, which are between the first-order sensitivity and the global sensitivity. The advantage of using full-link ANN combined with the improved Garson algorithm lies in the correlation between multiple performances. In contrast, the DMIM algorithm’s advantage lies in the full calculation of global sensitivity under the interaction of multiple parameters. Therefore, to ensure the accuracy of the analysis results, this paper mainly uses CWS and DMIM-delta as the main consequence of the discussion. To further check the performance of ANN Garson and DMIM-delta in sensitivity analysis, the calculation of correlation coefficient and error-index between the two sets of results is beneficial to better evaluate the reliability of the calculation results (Table 3).

3.3 Data analysis for sensitivity indexes

According to the sensitivity analysis results of different methods (Figure 7), all four calculation results can better identify the design parameters with significant sensitivity in the model, while there are some differences in the design parameters with low sensitivity. Generally speaking, the analysis can be divided into three situations: (1) Local sensitivity analysis CWS for the interaction among indicators of multiple performances (Figure 7a); (2) The global sensitivity DMIM-delta (Figure 7b) of the interaction among parameters of multiple designs, but the interaction among indicators multiple performances is not calculated; (3) Only consider the influence of a single parameter change on a single performance label RBD-S1 and DMIM-S1 (Figures 7c and d). Based
on the analysis of sensitivity index values, the envelope enclosure of residential buildings in this area has a high sensitivity on the five parameters of external shading components (S-D, S-N and S-A), south window-wall area ratio (WWR_S) and north window-wall area ratio (WWR_N). The sensitivity of S-D, S-N and S-A was significant, and the sum of them was >60% in various performance labels. The sensitivity of the sum of WWR_S and WWR_N was also >20%. And the sensitivity of the other design parameters is <20% accumulatively, which has little effect on the performance within the adjustable range.

4 Discussion

Due to the lack of operational data on building performance, it is hard to establish the building envelope performance model based on the real situation. Meanwhile, the operation data can only reflect the performance of a specific design portfolio. It is not easy to obtain the same result as the actual operation through simulation. Therefore, the simulation study can obtain the variation trend of various parameters which can accelerate the evolution process of modern architecture to adapt to the environment, and then promote the development of architecture towards sustainable development. Sensitivity analysis of the model can improve the interpretability
and simplify the complexity of the model.

In later research and practice, a more detailed model can be established according to the leading factors of the design. For example, shading measures and ventilation devices are used only in summer, and transparent enclosures utilise solar radiation as much as possible in winter which reduces heat loss at night. Besides, due to the numerous design parameters of the envelope structure, the comprehensive influence of more dimensional design parameters and performance labels should be studied in the later research to improve the model’s accuracy and applicability. On the choice of performance labels, computational fluid dynamics (CFD) may be combined to calculate indoor air quality and air distribution to optimise the indoor environment calculation model, while is also an expandable research programme.

Fig. 8 The prediction curve (P-C) of the ANN model.

5 Conclusion

This paper investigated the new energy demonstration zone of Turpan and established a multi-performance parameterised solution model under the action of multi-parameter coupling. LHS was used to generate samples of different combinations, and parameterised performance simulation tools were used to solve each combination. Through the sensitivity analysis and discussion of the results, the research conclusions are as follows:

1) The sensitivity analysis results of RBD-FAST and Dimim-S1 are almost the same, so it can be generally inferred that the calculation results of DMIM-delta have high reliability. Moreover, the results of DMIM-delta and ANN Garson’s calculation are highly consistent. Therefore, the calculation results of ANN Garson and DMIM-delta have certain reliability.

2) The envelope enclosure of residential buildings in this area has a high sensitivity on the five parameters of external shading components (S-D, S-N and S-A), south window-wall area ratio (WWR_S) and north window-wall area ratio (WWR_N). The sensitivity of S-D, S-N and S-A was significant, and the sum of them was >60% in various performance labels. The sensitivity of the sum of WWR_S and WWR_N was also >20%.

3) Draw P-C for the performance model established by ANN, which can better explain the performance model and further verify the correctness of sensitivity analysis results. From the curve, the four parameters of S_A, S_N, S_D and WWR_S have strong volatility. Through the analysis of the P-C, it can be seen that there is no optimal solution for the performance design of the residential building envelope in this area, and through the multi-objective optimisation method, it is necessary to obtain a reasonable parameter combination under
different dominant factors.

(4) After the sensitivity analysis process, the calculation efficiency of the model can be improved as far as possible without reducing the accuracy of the model in the later simplified calculation and multi-objective optimisation. Parameters with weak sensitivity can be set to a fixed value in the later optimisation process of the model to reduce the complexity of the model when the dimension of characteristic parameters is too high.

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