The Use of Normative Energy Calculation for Natural Ventilation Performance-Driven Urban Block Morphology Generation

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Abstract. Exploring the three-state coupling relationship between "urban block morphology, carbon emissions, and human comfort" is necessary when making preliminary design decisions. Currently, morphology generative design is subject to interactions between the level of model definition and simulation duration. Self-intelligent and intelligent generative design workflows using evolutionary algorithms are now becoming an effective solution to this problem. This paper incorporates a dedicated controllable ventilation model based on a normative performance calculator and proposes it in the morphology feedback generation execution of the automated design process. The aim is to develop this automated design method from ambient environment driving only to outside-interior coupling natural potential ventilation influencing morphology generation, with the aim of providing technical support for carbon emission performance-oriented and indoor human comfort-oriented design of urban blocks.

Keywords: Generative design · Urban block morphology · Quantification method · Natural ventilation

1 Introduction

"Double carbon" drives spatial generative design, and digital empowers street-level smart growth. While meeting the people's growing demand for building comfort, controlling the growth of building energy consumption is one of the keys to achieving the "dual carbon" goal. Building operation energy consumption accounts for 22% of China's total social energy consumption, and construction energy consumption accounts for 11%. In the Reshaping Energy Scenario in 2060, the emission reduction potential of the construction industry is 74%, which is 1.5 times that of the industry, accounting for the largest proportion of the three energy consumption industries, and it will contribute approximately 50% to the peak of carbon emissions ahead of schedule. Energy savings [1]. Taking into account the impact of urban microclimate on the energy consumption of buildings, conducting research on space self-generating design methods is conducive to comprehensively weighing building energy consumption and digitally empowering

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urban smart growth. The fourth generation of urban design should aim at the theoretical reconstruction of morphological integrity and take the transformation of digital technology methods and tools of human-computer interaction as the core feature [2]. The expression paradigm of urban planning and architectural design based on computational design thinking is promoting the evolution of traditional space construction and environmental materials in the direction of "performance-driven form" intelligent design. Low-carbon urban planning at the macro level, sustainable block design at the meso level, and green building design at the micro level all contribute to the establishment of a resilient living environment. With the help of artificial intelligence tools, planners and architects can break through the shackles of this linear science prior to construction activities and Post-occupancy evaluations, the high point locates the urban space [3, 4].

1.1 Core Algorithm of Carbon Emissions

The core of calculating carbon emissions during the operational phase of a building complex is building energy consumption calculation. Based on the direction of data aggregation, existing Urban Building Energy Modelling (UBEM) algorithms for street-block building complexes can be divided into top-down and bottom-up approaches. The latter focuses on individual building energy consumption rather than overall regional building energy consumption modeling, which results in higher accuracy and facilitates the evaluation of the impact of new standards and technologies on building energy consumption in a "dual-carbon" direction, but is relatively time-consuming. The bottom-up approach can be divided into physical methods and data-driven methods, with physical methods further divided into detailed physical models and simplified engineering models. The scale of calculating street-block building complex energy consumption is much larger than that of single building energy consumption calculation. Compared with detailed physical models, engineering models are easier to program, operate more quickly, and can be better combined with data-driven models, embedded in building intelligent design workflows, and support "dual-carbon" driven spatial generation research [5].

It is generally believed that engineering models are inferior to physical detailed models in terms of computational accuracy due to the simplification of computational conditions. However, Godfried Augenbroe et al. [6–8] pointed out that some engineering models are not less accurate than detailed physical models when supporting building performance calculations in the planning and design stages, i.e., solving the Fuzzy Topology problem in the conceptual phase. In fact, they even demonstrate better robustness in comparative studies. There are two main reasons: (1) the design stage is a process where conditional information is constantly input, increasing the amount of graphic information and decreasing abstraction. The quantity, form, and quality of space are interdependent and restrictive, constantly changing, and the amount of quantifiable building information is limited. At this stage, a large number of key parameters must be assumed in order to carry out targeted modeling (Design Performance Modeling, DPM). Therefore, there is a possibility of calculation deviation due to insufficient assumptions. (2) Detailed physical models also require assumptions and simplifications, which can also increase calculation deviation. De Wit et al. conducted research on the impact of uncertainty factors caused by this simplification on building energy consumption simulation, proving that this impact cannot be ignored in most cases.

Table 1. Classification of core algorithms for urban building energy consumption

Algorithm			Model tool
Top down			Establish the relationship between long-term historical data of the market, economy, sociodemographic and urban energy consumption without the need for a detailed technical description
Bottom-up	Physical method (forward simulation)	Physically detailed model (white box model)	EnergyPlus, etc. ISO 13790, etc.
		Engineering simplified model (gray box model)	
	Data-driven approach (reverse simulation)	Data-driven model (black box model)	Multiple linear regression model, artificial neural network model, etc.

Hence, the proposed intelligent and shape-based workflow in this project will employ a “grey box model” (engineering model) rather than a “black box model” (data-driven model) during the critical phase of building performance calculation. This will enable the completion of building performance evaluation, encompassing the carbon emissions index as well.

1.2 Carbon Emissions Calculation Platform

The existing engineering models for energy consumption analysis of urban building groups are mainly based on the classic IS013790 algorithm. ISO13790:2008 provides 3 calculation methods for the design and evaluation of the thermal and energy performance of buildings with different degrees of complexity: monthly steady-state calculation method, simple hour-by-hour dynamic calculation method (quasistatic), and detailed dynamic simulation method [9]. The main building energy consumption calculation platforms based on this algorithm include SimStadt, a 3D urban energy platform developed based on the GIS database, which can provide energy consumption analysis of building stock or individual buildings. The 3D spatial urban energy consumption simulation method developed based on 3D urban morphology data can support the evaluation of solar energy potential and heating demand of residential buildings. Urban Energy Maps, a residential energy consumption and greenhouse gas emission calculation platform based on a GIS visualization module, can provide local governments with energy performance monitoring of urban buildings. These software programs do not support real-time calculation and editing.

The Energy Performance Calculator (EPC, ISO13790) software ecology based on the standardized calculation method of quasistatic building energy consumption provides a new way to calculate the carbon emissions of urban buildings in the solution design stage [10, 11]. Among them, the calibration add-in EPC_Calibration Add-In, which is used to correct the difference between the assumed value and the real value of the parameter, solves the problem of limited building information in the early design stage. As shown in Fig. 1, the software ecosystem provides seven main energy consumption calculations for building operations (heating, cooling, humidification, lighting, pumps, fans, hot water; heating, cooling, humidifying, lighting, pumps, fan, domestic hot water) and is able to convert that into carbon emissions. Its computational accuracy has passed the dynamic simulation comparison experiments under different model information granularity. Among them, Mayuri [12] and Kokogiannakis G. [13] studied the commonality and characteristics of EPC and physical detailed models ESP-r, EnergyPlus, and IDA-ICE in the calculation of building operating energy consumption. Adrian C. et al. [14] studied the application range of different precision calculation methods and refined simulations based on ISO 13790 in heating and cooling energy consumption calculations. Qi L. et al. [15] studied the influence of uncertain factors on building performance calculation under different urban scales, and compared the accuracy of steady-state calculation and refined finite element numerical simulation. Research proves that EPC is as accurate as or better than physical detailed models during the conceptual design phase [10, 15]. In addition, some scholars have indirectly verified the applicability of software ecology by applying EPC to specific engineering problems. For example, Ji-Hyun Kim, etc. [16] EPCs were used for LEED-EAc1 scoring. Sang Hoon L. et al. [17] used EPC to evaluate the performance of residential buildings. Therefore, based on EPC software ecology, this project develops an efficient calculation method for the energy consumption of street buildings. Here, the quasistatic calculation method is mainly used.

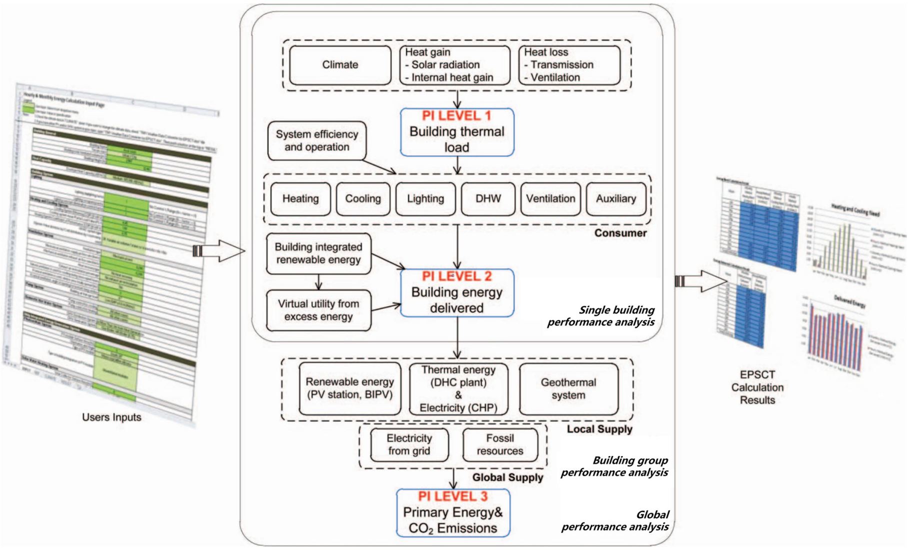

Fig. 1. Schematic diagram of EPC [17, 18]

1.3 Calculation Path of Carbon Emissions

The difference between the research plans for carbon emission calculation mainly lies in the strategy selection of thermal zoning, heat transfer model and algorithm in the thermal simulation step. It is generally believed that for the severe and cold climate areas where heating is the mainstay and the urban building types are relatively simple (such as residential buildings), the steady-state heat transfer model can be used to calculate the heating energy consumption indicators of various benchmark buildings, and then according to the total amount of various types of buildings (the number of buildings or building area) is used to weight the estimated subitems and overall energy consumption; for cities with a large proportion of cooling demand, such as hot summer and cold winter, hot summer and warm winter, and the building types are diverse or functionally complex when it is higher, a multizone dynamic heat transfer model should be used [19].

Automated building thermal zoning algorithms such as Autozoner can achieve rapid thermal zoning of a large number of individual buildings in urban areas. However, this method cannot incorporate microclimate factors in the classification and characterization; that is, considering the local environmental impact of the city and the spatial morphological characteristics of the building itself, clustering or typological standard unit settings are performed. In this regard, the academic community has made cutting-edge explorations in classification optimization. Cambridge University's light and thermal (LT) method [20] pioneered the physical calculation of energy consumption and urban form analysis separately: based on the parameters obtained by the form analysis, the corresponding energy consumption values were extracted from the LT curve set database, and then the overall energy consumption of the region was calculated by the interpolation method. This method makes many simplified settings in terms of climate boundaries, equipment planning and so on. MIT's shoebox algorithm (Shoeboxer)[21] On the basis of LT, the calculation accuracy is improved, and single building (unit) partial clusters with similar thermal characteristics (function, orientation, external occlusion, etc.) are merged into large regions, and the energy consumption intensity of the corresponding representative unit modules (so-called "shoeboxes") in each region is calculated and weighted. The algorithm requires that the indoor temperature setting of each partition is not very different, and the clustering standard is set reasonably. Building Block Energy Estimation (BBEE) of Tsinghua University [22] It consists of two parts: a typical zone and an energy database. Among them, the typical thermal area is similar to the unit module in the shoebox algorithm; the energy consumption database is similar to the LT-Curves database in the LT method. The corresponding database lookup table is performed for the energy consumption of each typical thermal zone, and the weighted summation of the energy consumption of all zones is carried out. Georgia Tech's EPC ecology uses the LT method of separating the architect's work from the engineer's, continuing the precision advantage of Shoeboxer's physical simulation of typical thermal zones. The EPC software has a partitioned and hierarchical energy consumption calculation design [10, 23]. Furthermore, its regional energy performance calculation software (Network energy, NEP) takes into account the accuracy of energy consumption calculation in the case of energy supply interaction between regional buildings (such as energy allocation during peak energy consumption) [17]. Due to the limitations of time and energy, the interaction mechanism of energy supply among regional building groups is not within the scope of this paper.

Based on the digital workflow for building generation driven by outdoor wind environment material performance, this paper incorporates the developed normative building energy consumption calculation method ventilation module to explore the formation of a new workflow for building generation driven by the coupling of indoor and outdoor wind environment material performance.

2 Methodology

2.1 Shape Path

The overall research approach for the study of the morphology generation of urban center spaces with wind and environmental performance orientation through the coupling of form-carbon-human is shown in Figs. 2 and 3. In terms of "form", the aim is to control the parameters of building clusters under wind and environmental conditions. In terms of "carbon", the potential for natural ventilation energy saving during the operation stage of each generated building cluster is calculated. In terms of "human", outdoor pedestrian wind environment comfort and indoor comfort are taken into consideration. In order to study the central area of the coastal new city, machine learning is used to establish the street pattern model of the city, and natural ventilation-related variables and evaluation methods are systematically set in the development of the calculation model. This paper proposes the incorporation of a dedicated controllable ventilation model based on a normative performance calculator into the automated design process for morphology generation.

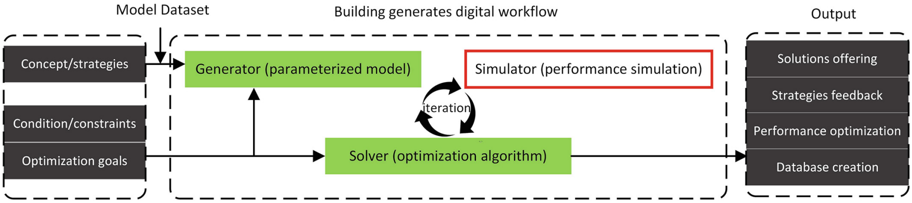

Fig. 2. Schematic diagram of the generative design method to be established

2.2 Development of Efficient Computing Methods

The research focus of this article is how to transmit the information of the outdoor wind information to the indoor environment. To this end, we opened an input value on the calculator with is detailed explain as follows, which is converted from the outdoor wind pressure and wind speed value. Then, indoor fresh airflow-related calculations are carried out, and finally, the delivered energy and carbon emissions are obtained.

Ventilation scene.

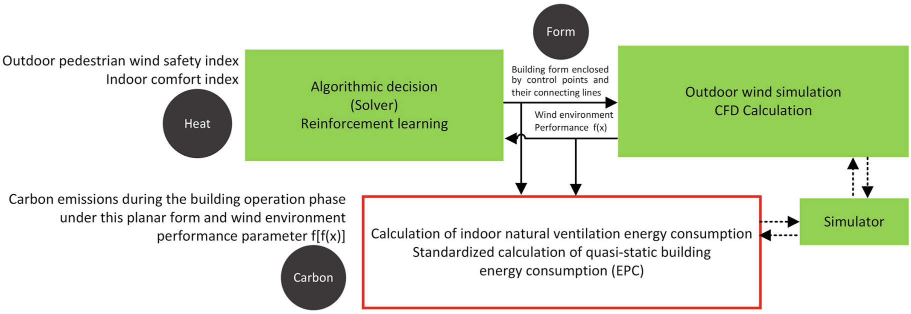

Fig. 3. Schematic diagram of "shape-carbon-human" coupling mechanism

Hybrid ventilation scene. In a hybrid ventilation (HV) scenario, natural ventilation is utilized to partially meet the cooling and fresh air requirements, based on a predefined outside air humidity threshold (either 70% RH or 80% RH). During every hour when the interior temperature (T_{in}) is higher than the ambient temperature (T_{am}) and cooling is required, the full cooling demand is met through the utilization of outside air. This approach is employed to determine the maximum potential of natural ventilation, assuming that the necessary air exchange can meet the cooling and fresh air requirements during these hours, even with a small temperature difference. However, outside of these hours, both cooling and fresh air are supplied by the mechanical system.

In this case, it is assumed that window opening control strategy is required in the simulation model. The reason behind this assumption is that during every hour when there is a cooling load and the interior temperature (T_{in}) is maintained at the set point temperature (T_{set}) by the mechanical cooling system, the complete cooling load is met through ventilation with outside air, provided the ambient temperature (T_{am}) is lower than T_{in}. This assumption is considered as the best-case scenario and referred to as the ‘cooling potential.‘ However, achieving this cooling potential in the actual building depends on various factors, such as the window opening size and orientation relative to the prevailing wind direction, which are determined by the final design provisions.

In the case of active dynamic control of window opening strategy, the Energy Performance Calculator (EPC) includes this feature in the simulation model. An ‘abstract’ ventilation provision is assumed, where at full opening ratio, a ventilation flow of X air changes per hour (ACH) is achieved.

Our logic is as follows: if the interior temperature (T_{in}) is above the target and higher than the ambient temperature (T_{am}), we allow an appropriate amount of outside air to enter the building through partially open windows. In the PNV case, a minimum amount of fresh air is always supplied naturally. We have added this scenario to the EPC, and our control logic determines when windows should be closed or partially open. The window opening ratio (V_{ratio} [m^2]) is determined as follows:

$$V_{ratio} = \begin{cases} C * ((T_{in} - T_{set})/(T_{in} - T_{am})), if T_{in} > T_{am} \\ 0, otherwise \end{cases} \quad (1)$$

Here, T_{in} [°C] is the interior temperature, T_{am} [°C] is the ambient temperature, and T_{set} [°C] is the temperature set point (or rather, target point) for cooling. To avoid undercooling, particularly at night, we use Eq. (1) to gradually adjust the opening ratio and make optimal use of outside air while maintaining proximity to the target temperature. The amplification Factor C is introduced to regulate the speed of the controller's response to temperature differences.

The absolute PNV ratio ($V_{abratio}$ [m^2]) is derived according to Eq. (2), which simply guarantees that its value remains within the range of 0 to 1.

$$V_{abratio} = \begin{cases} 1, if V_{ratio} > 1 \\ 0, if V_{ratio} < 0 \\ V_{ratio}, otherwise \end{cases} \tag{2}$$

The flow volume of fresh air (V_{fresh} [m3/s]) is derived according to Eq. (3).

$$V_{fresh} = \begin{cases} V_{max} * V_{abratio}, if V_{abratio} > 0.01 \\ 0.01 * minimum, otherwise \end{cases} \tag{3}$$

V_{max} [m^3/s] is the maximum airflow with fully open windows, as defined by the modeler. In theory, differences in the value of X will have only a small effect, as long as X is greater than 10. When the windows are fully open, the room temperature will quickly follow the outside temperature. Maximum air flow rate V_{max}, as well as amplification factor C could be adjusted according to specific circumstances, if necessary, by using adaptive parameters, such as using machine learning algorithms to automatically determine the C and the V_{max} based on historical data.

$(V_{ratio} * V_{max})$ * h * ρ * cp * $(T_{in} - T_{am})$(4)

Q_{cool} represents the energy required for cooling. Air capacity represents the cooling capacity of air per unit time. The air capacity is represented by the product of the heat transfer coefficient h per unit area, the density ρ of air, and the specific heat capacity cp.

Furthermore, we would like to discuss the opening activity(V_{open}) and position($V_{position}$) of windows on building facades. Firstly, building designs driven by natural ventilation performance as one of the main factors may not allow for the possibility of hinged windows (including those opened by occupants). It is generally assumed that the target building is equipped with a self-control system for windows. The term "windows" refers to the windows and their variations that face the outside of the building, such as the linear opening integrated into the window frame proposed by Godfried Augenbroe et al. [24]. These buildings use natural ventilation as a cooling source instead of mechanical ventilation, partially or completely, through the self-control system for windows, based on a whole-air conditioning system. This achieves energy savings without compromising thermal comfort. Secondly, when considering the position of windows, safety, and comfort in outdoor wind environments are generally the main factors considered based on regional building regulations. For example, Philip F. Yuan et al. [25] used factors such as average wind speed at pedestrian height, the ratio of comfortable wind speed at measurement points, wind speed dispersion, the ratio of calm areas, and the ratio of strong wind areas to generate the morphology of building clusters.

Evaluation measures

The following criteria were used to evaluate the HV performance of a building:

Measure HV-1: The factor of available hours for free cooling (R_{hour}) is derived according to Eq. (5).

$$R_{hour} = \frac{H_{vent}}{H_{novent}} \tag{5}$$

H_{vent} [h] is the annual total number of hours when the cooling need is completely covered by means of outside air, and H_{novent} [h] is the annual total number of hours when the cooling need cannot be covered by means of outside air.

Measure HV-2: The factor of the cooling load reduction ($R_{cooling}$) is derived according to Eq. (6).

$$R_{cooling} = \frac{E_{novent} - E_{vent}}{E_{novent}} \tag{6}$$

E_{vent} $[kWh/m^2]$ is the annual cooling energy need with the use of natural ventilation, and E_{novent} $[kWh/m^2]$ is the annual cooling energy need without the use of natural ventilation.

3 Results

By displaying the carbon emission results with or without natural ventilation in the result input column, the natural ventilation potential is displayed (Figs. 4 and 5). Furthermore, this potential is used as a reward value to participate in iterative morphing. The main changes in the design process related to the new incorporated ventilation model are as follows.

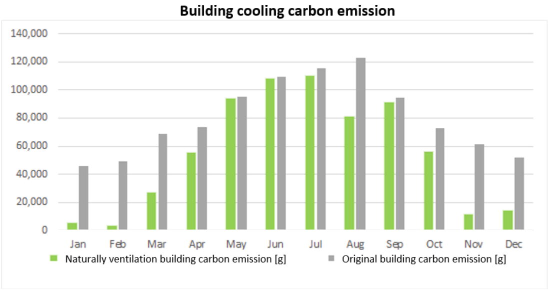

Fig. 4. Building cooling carbon emission

(1) **Establishment of the Parametric Model of the Street Profile Space Building Environment.**

Typical block model refinement. Induction of different types of typical city blocks for random sampling and construction of a numerical simulation database. Through manual discrimination, partial clusters with similar thermal characteristics (function, orientation,

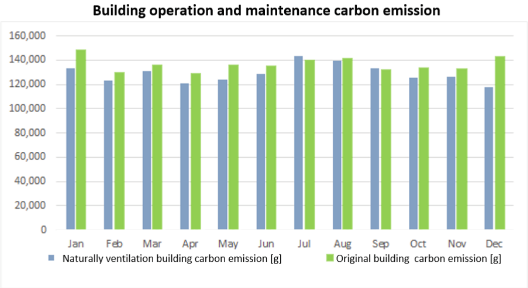

Fig. 5. Building operation and carbon emission

external occlusion, etc.) of the individual buildings in the prototype block are merged into a large area. For these large area types, preset the corresponding EPC (quasistatic high-efficiency calculation mathematical model for the carbon reduction potential of natural ventilation in buildings) input parameters (Fig. 6), and establish a corresponding database set There are two main types of parameters: I related to the indoor comfort maintenance of a single building and II related to the external protective structure of a single building.

Fig. 6. Parameter setting of thermal zones in a large area

(2) **Construction of a mathematical model for the comprehensive evaluation of the carbon reduction potential of natural ventilation in buildings.**

Mainly through formula derivation and computational fluid dynamics simulation comparison experiments, the sensitivity parameters of the natural ventilation potential of different types of buildings are clarified; through mathematical model construction, the relationship between the sensitivity parameters of the natural ventilation potential and the corresponding performance indicators is defined; through the research and development of efficient calculation methods for the natural ventilation potential, a collaborative design platform for building performance evaluation is built (Fig. 7).

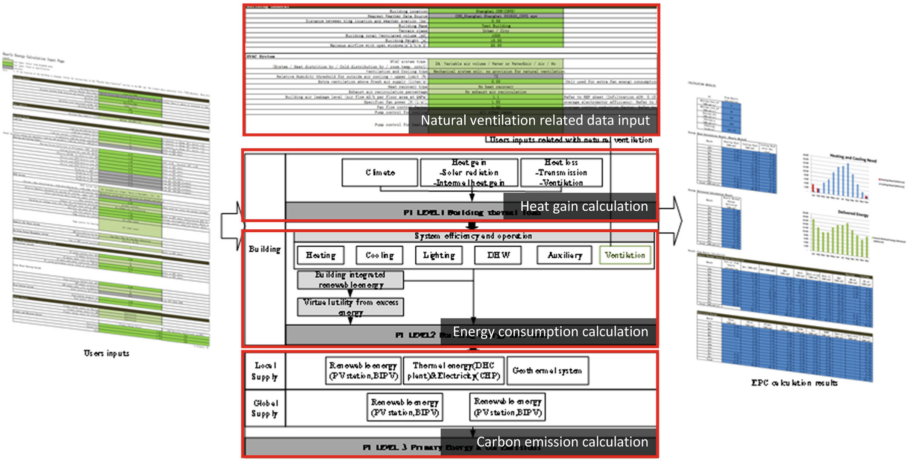

Fig. 7. Basic framework of comprehensive evaluation mathematical model

Development of an efficient calculation method for natural ventilation potential. The EPC building performance evaluation advantage platform is used to embed the control logic related to the sensitivity parameters of building natural ventilation potential and develop an efficient calculation program EPC_v_H2.0:NV.

a. Carry out research on the logic programming of natural ventilation scenario design and evaluation criteria.
b. Research on key influencing factors of natural ventilation and system automatic control logic programming.
c. Interface settings for reasonable translation of space form and outdoor wind environment to efficient computational mathematical models.

(a) Mechanical parameters for each shape scheme of the agent processing.

Through the establishment of input parameters, the translation of relevant outdoor environment information to the indoor environment is completed. There are two main types of parameters: I is related to the general situation of a single building, and II is related to the thermal calculation of a single building.

(b) Wind environment data for each shape scheme of the agent processing.

Through the establishment of input parameters, the translation of relevant outdoor environment information to the indoor environment is completed. There are two main types of parameter sets: I related to the outer protective structure of a single building and II related to the climate information of the location.

(3) **Genetic algorithm-driven iterative optimization and application testing.**

The values of the design parameters are controlled by a genetic algorithm. The following two indicators are set as the control parameters at different levels of the optimization target, and the iterative optimization calculation is performed to obtain the optimal solution of the target building space design.

a. Urban level: wind environment comfort, average sunshine duration on winter solstice, urban building density and urban traffic space density.
b. Building level: the building performance evaluation system index including the carbon emissions of the building group.

Examine the effectiveness of the EPC_v_H2.0: NV system in assisting design, especially how the system can provide architects with "task-specific" (task-specific) under different design conditions (site, building type) and different optimization goals. Specific) the feasibility of optimizing the results.

4 Conclusion

Timely feedback of relevant information to architects and engineers during the primary design phase is crucial to overcome the limitations of empirical knowledge and achieve a performance-informed and performance-aware design process. Design Performance Modelling (DPM) facilitates rational dialogue, and this case study utilizes a normative energy calculation method, the EPC, to go beyond the performance rating of building design strategies as the context and purpose of the dialogue are constantly changing. This paper introduces a dedicated controllable ventilation model based on a normative performance calculator and proposes it in the morphology feedback generation execution of the automated design process. The aim is to develop an automated design method that goes from ambient environment driving only to outside-interior coupling, natural potential ventilation influencing morphology generation. This will provide technical support for carbon emission performance-oriented and indoor human comfort-oriented design of urban blocks.

Architecture-related studios and firms, such as the Architectural Intelligence Group (AIG), Digital Future Studio (DF), and AECOM iLAB (Innovation Laboratory), have shifted their focus to the primary design stage in response to the expectations expressed by owners and occupants, and their fulfillment by designers and building operators. Some of these firms even attempt to replace the work of designers by utilizing machine learning for intelligent management of design elements, architectural drawing recognition, and generative design for spatial form. However, building performance-driven design should strengthen human capacity, meaning that it should not only serve as an intuitive ruler to quantify design but also broaden designers' sense organs to provide better value. In other words, we advocate that architects should possess programming knowledge to achieve the most appropriate performance calculation and expand their design thinking to the field of software creation. Providing this support is essential to avoid limiting the human mindset with software constraints.

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