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A machine learning-enhanced design optimizer for urban cooling

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Abstract

Urban cooling becomes a priority in urban planning and design practices. Limited by the slow running speed and prescriptive nature, existing computational tools such as simulation and optimization are yet to be fully integrated in the design decision-making process. This paper describes the Machine Learning-Enhanced Design Optimizer (MLEDO), a novel workflow in search of optimal design option for urban cooling. A physics-based simulation model was developed to assess the cooling performances of a large database of urban design variations. The database was used to train an Artificial Neural Network model, which was then linked with a Genetic Algorithm to rapidly identify optimal design options. The MLEDO workflow was evaluated using a new development urban site against a traditional Simulation-based Genetic Algorithm Design Optimizer (SGADO) as well as human designers. MLEDO outperformed the latter two in terms of efficiency and the performance of the optimal design options. It can also quantify the importance of design parameters in their contribution to cooling performances, which can be used to enhance the understanding of human designers and inform design revisions. MLEDO has the potential to be further developed into a software tool in support of early-stage urban design.

Keywords

Machine learning, urban form, heat stress, simulation, genetic algorithm

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Introduction

Cities are becoming warmer, driven by the Urban Heat Island (UHI) effect and extreme weather conditions from climate change. A warmer city imposes higher levels of heat stress on its residents, raising morbidity and mortality,[1,2] limiting outdoor activities and reducing the quality of life. Recent studies suggest that effective urban design can significantly reduce pedestrian heat stress and increase opportunities for outdoor activities in open spaces in humid subtropical weather.[3,4] Urban designers and policymakers have stepped up efforts to meet the heat challenge in recent years. Examples include Hong Kong's Air Ventilation Assessment (AVA), a mandatory procedure for major public development projects to enhance urban air ventilation[5]; urban design practitioners have experimented with innovative design features for urban cooling, such as vegetation, urban geometry, shading, water features, materials and surfaces, which have been highlighted in the Cooling Singapore[6] collaborative research initiative.

Emerging computational tools such as simulation and optimization have played an important role in urban cooling design. Simulation models based on first principles; that is, energy conservation equations applied at the

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neighbourhood, building and room scales, together with optimization algorithms, have been used increasingly to assess risks associated with urban heat. Meanwhile, progress in design optimization research enables design problems to be formulated mathematically and to be optimized given pre-defined objective functions and various constraints. Despite progress, computational tools have not been fully integrated in the design decision-making process for urban cooling. Given the complexity of urban features, including building massing and layout, surface materials and greenery, the first-principle simulations for urban cooling performances are computationally expensive, which limits its usage within practical deadlines. Compromises are needed for either using a shortened period of assessment,[3] or relying on laboratory equipment such as the cluster computers,[7] as the calculation load exceeds the capacity of ordinary personal computers. Simulated results do not automatically suggest how to improve the design; rather, a designer needs also to resort to personal experience, intuition, or guesswork. Nor do simulated results indicate a reasonable performance benchmark under the site constraints. On the other hand, design optimization, although advancing in recent times, has not been widely adopted by real-world practice.[8] One of the obstacles is the high calculation cost due to large number of calls to simulation models.[9] Another barrier lies in the prescriptive nature of design optimization, in which an optimal design option is produced without justifications,[10] making it difficult to be implemented in practice where revisions are necessary over multiple priorities and stakeholders. There is a need to develop new tools to bridge the gap between computational tools and design decision-making to better support the design of more liveable, sustainable and resilient cities.

In this study, a Machine Learning-Enhanced Design Optimizer (MLEDO) tool is developed to automatically identify optimal design options in cooling performance. The aim is to reduce the computational load of a traditional simulation-based design optimization by blending machine learning methods. A large database of design options and its urban cooling performances are prepared using a multi-scale simulation model. A Neural Network-based Surrogate Model (NNSM) was developed to predict the cooling performances of design features, which was further linked with a genetic algorithm to improve the optimization performance of evolutionary algorithms. The MLEDO approach was applied in a design case in the humid subtropical climates in Southern China. The results are compared with optimal options from a traditional simulation-based optimization and from human designers.

Relevant works

Simulation-based design optimization has emerged as an important field in recent years, although applications in urban cooling design are rare. Research advancement in the simulation of the urban thermal environment, optimization and machine learning provides new opportunities to better integrate computational tools in the design decision-making process.

Simulation-based design optimization

A large number of simulation models have been developed to assess aspects related to urban cooling performances. Most are based on first-principle methods, that is, energy conservation equations applied at urban and building scale. Notable software tools including ENVI-met,[11] Rayman Pro,[12] the Outdoor Comfort Calculator of the Ladybug Tools[13] and CityComfort+[14] have been used to evaluate the cooling potential of design features on external thermal comfort. The majority of studies rely fully or partially on the Computational Fluid Dynamics (CFD) method, which is the primary tool applied in urban microclimate analysis.[15,16] A drawback of the first-principle methods, despite great merits, is their relative slow running speed,[10] making them ill-suited to the purpose of an optimization algorithm. For this reason, researchers experimented with empirically derived methods to approximate the behaviour of a first-principles simulation. For instance, Wang et al.[17] developed the Design-Based Natural Ventilation Potential Index, which allows designers to make better decisions for natural ventilation potential without extensive CFD runs. Hu et al.[18] developed optimization algorithms to manipulate the Sky View Factor values in order to mitigate UHI under urban density constraints, such as the limit on building height, floor area and building setback distances.

Research on simulation-based design optimization has made progress in recent years. Mathematical methods have been developed to automatically generate and evaluate design options against pre-defined criteria, such as building energy performances, structural weight and financial returns on investments. A commonly studied method in architecture, urban design and urban planning is the Genetic Algorithm (GA),[19] a biologically inspired optimization algorithm mimicking the natural selection process,[20] in which organisms adapt themselves to the changing natural environment,[21] alternatively known as 'the survival of the fittest'.[22] This method is used in the area of urban design and planning.[23–25] Only a handful of studies have used simulation-based design optimization for urban cooling performances. Chen et al.[26] used GA and coupled simulation models of heat convection, radiation and conduction to identify the optimal design options of buildings and trees to reduce heat stress for an urban area in Japan; A two-step optimization workflow, first to perform a rough calculation based on coarse CFD mesh to select high-performing options, and then to conduct a precise simulation with fine meshes, was adopted in order to reduce the calculation load, which limited the number of design options placed under refined simulation. Bajšanski et al.[13] used GA and the UTCI calculator based on the Rhino-Grasshopper software platform to optimize the urban design of a street canyon site. The objective function is outdoor thermal comfort, although the localized wind effect was not considered in the calculation. Quan et al.[27] combined GA and simulation models in search for optimal design options based on building energy and pedestrian thermal comfort. The study was limited by a set of simplified design parameters, while localized wind effect was not included in the calculation of urban cooling performances. Two studies, Du et al.[28] and Kaseb et al.,[29] used GA and CFD simulations to identify optimal building design in terms of urban wind comfort, although air temperature, thermal radiation and humidity are not included in the assessment of urban cooling performances.

Machine learning-based design optimization

Advancement in machine learning algorithms provided new opportunities for design optimization in the field of architecture, urban planning and urban design. The neural network model, a type of algorithm mimicking biological neural system, has been used in prediction of performances from building energy use to occupant behaviours. A popular machine learning method is the Artificial Neural Network (ANN) model, which consists of layered structures of interconnected neurons, mimicking the biological systems of the human brain.[30] ANN is used to predict energy building consumption. Examples include the study by Neto et al.,[31] which found that an ANN model can yield more accurate prediction (in agreement with metered data), compared with simulated results using EnergyPlus, the state-of-the-art building energy model.

A number of explorative studies have combined ANN with GA to replace the time-consuming simulation model and to enhance the performance of design optimizations. Magnier et al.[9] used an ANN-enhanced GA to optimize the design of building envelope and HVAC systems, leading to optimal design with improved occupant thermal comfort and reduced energy consumption. Zhang et al.[32] combined GA, ANN, a multivariate regression model, a fuzzy logic controller and a CFD Tool to optimize indoor thermal comfort, air quality and energy consumption. Asadi et al.[33] developed a neural network tool combining GA and ANN to quantitatively assess technology choices in a building energy retrofit. Gossad et al.[34] used GA and ANN to optimize the thermophysical properties of external walls of a dwelling in order to improve their thermal efficiency. In a pioneering study, Weerasuriya et al.[35] integrated an ANN model with GA to optimize pedestrian thermal comfort or wind comfort near a building with elevated ground floor. The strength of combining ANN with GA, as it is reported by these studies above, lies in the enhanced computing speed compared with, say, the simulation-based approach. While promising, the ANN and GA methods are yet to be applied at a larger scale to assess the cooling performance for a cluster of buildings or an urban neighbourhood.

Research gaps

Computational tools have yet to be fully integrated into the design decision-making process in urban cooling design. First-principles simulation models are computationally expensive and have not been fully incorporated in design development and design thinking process.[36] Simulation results alone do not provide solutions[37] nor do they fully answer the question as to why a design fails or succeeds.[38] Rather, a designer also needs to resort to personal experience, intuition or guesswork. On the other hand, design optimization, although advancing rapidly in recent decades, is yet to be widely used by design practice partially due its prescriptive nature: the output is an optimal design option without justifications, making it difficult to be implemented in practice, where repeated revisions are necessary with multiple priorities and stakeholders. Another barrier lies in the high calculation load for simulation-based optimization algorithms.[8] The Genetic Algorithm, for instance, requires a large number of calls to the evaluation function,[9] which makes it computationally expensive. Researchers are left with an undesirable trade-off of either choosing a quick, often over-simplified simulation model,[26] or compromising for the sub-optimal options based on a small number of GA population/generations.[39] There is a need for a new method combining the strengths of simulation-based optimization and the fast-running machine learning algorithms. The new method should not only generate the optimal design option(s), but also inform users about the relative importance of key design parameters in their contribution to the cooling performance. Such a method can better support for the design practice of more liveable, sustainable and resilient cities.

Methods

A novel optimization framework, that is, the Machine Learning-Enhanced Design Optimizer (MLEDO), was developed in response to the research gaps. Its conceptual framework is summarized in Figure 1. In the model training phase, a database was produced using simulation models and a design generator, which consists of a large range of design variations and simulated urban cooling performances; the database was then used to train and evaluate a machine learning model. In the design optimization phase, the machine learning model was linked to a genetic algorithm to identify the design option that results in the best

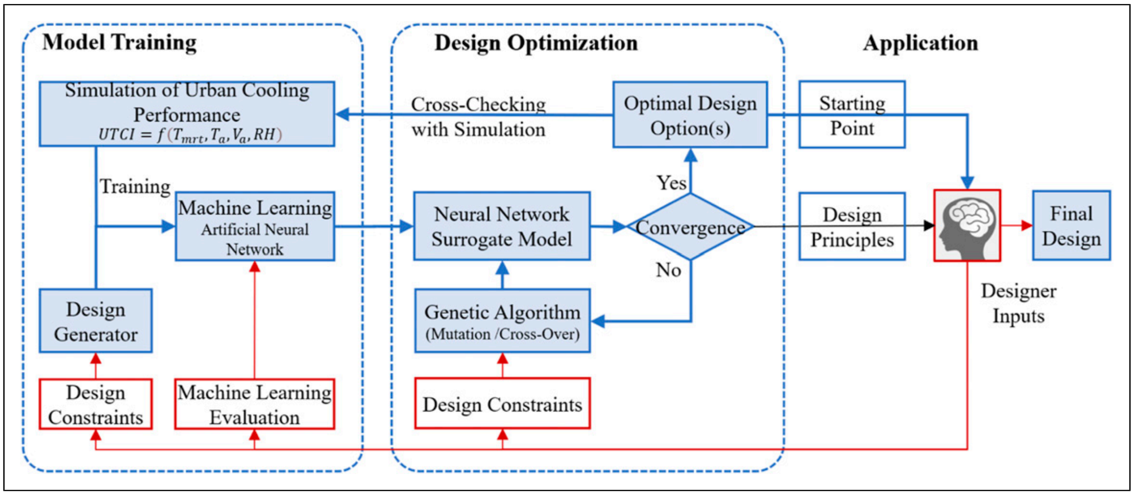

Figure 1. A conceptual framework of the Machine Learning-Enhanced Design Optimizer (MLEDO).

cooling performance. The optimal design was cross-checked with the simulation of the specific design option and the best design from human designers. The MLEDO can also generate design principles by ranking key design parameters that are most significantly linked to cooling performances. This was then used as a starting point for the final design, incorporating features from best-performing human designers. As a pilot study, the MLEDO approach was applied for a new development urban site. A design game was held in parallel, participated by human designers using the identical site layout, design constraints and objectives. The performances of design optimization algorithms with and without machine learning were compared with each other.

Model training

A simulation model was developed to assess the outdoor thermal stress at pedestrian level. A surrogate model based on neural network was developed to reduce the calculation load of the simulation model.

Simulation of urban cooling performance

A simulation model was developed to assess the urban cooling performance, measured as outdoor thermal stress at pedestrian level. The model components consist of the mean radiant temperature, air temperature, wind speed and human biometeorology (Figure 2).

The mean radiant temperature was modelled using reverse ray-tracing methods by the CityComfort+ method, a reverse ray-tracing algorithm, which accounts for radiative energy from direct, diffuse and reflection solar radiation as well as long-wave radiation from the atmosphere and solid surfaces. The advantage of the CityComfort+ method compared with others such as SOLWEIG or Rayman Pro, is that it has shown reasonably good agreement with measurement data, and it allows for vector-based geometries inputs, and it can be easily linked to Rhino software platform and optimization algorithms. The in-situ T_{mrt} can be expressed in equation (1) below according to Huang et al.[14]

$$T_{mrt} = \sqrt[4]{\frac{1}{\sigma}\left(a_p \cdot E_{sol} \cdot F_{sol\rightarrow p} + \varepsilon_{sky} \cdot E_{sky} \cdot F_{sky\rightarrow p} + cE_{urb} \cdot F_{urb\rightarrow p}\right)} \quad (1)$$

where σ is the Stephane–Boltzmann constant; a_p is the absorption coefficient of solar radiation for a person; E_{sol} is the solar radiation intensity; E_{sky} is the long-wave radiation intensity of the sky; E_{urb} is the long-wave radiation intensity of the urban surface; $F_{sol\rightarrow p}$ is the view factor between the short-wave sources and a person; $F_{urb\rightarrow p}$ is the view factor between the urban surface and a person; ε_{sky} is the emissivity of the sky and ε_{urb} is the emissivity of the solid surface. The above method has been evaluated using field measurement data, with satisfactory agreements observed between simulated and measured data.[14] The input parameters in T_{mrt} simulation are listed in Table 1.

Localized air temperature (T_a) was modelled using the Screening Tool for Estate Environment Evaluation (STEVE), which was empirically derived and evaluated in Singapore,[40] and subsequently validated in Guangzhou, China.[41] The STEVE formula was used to predict the daily minimum (T_{min}) and maximum (T_{max}) air temperature of a point based on urban form parameters and ambient meteorological data, as it is shown in equations (2) and (3)

$$T_{min} = 4.061 + 0.839\, T_{min}^{Ref} + 0.004\, PAVE - 0.193\, GnPR - 0.029\, HBDG + 1.339*10^{-6}\, WALL \quad (2)$$

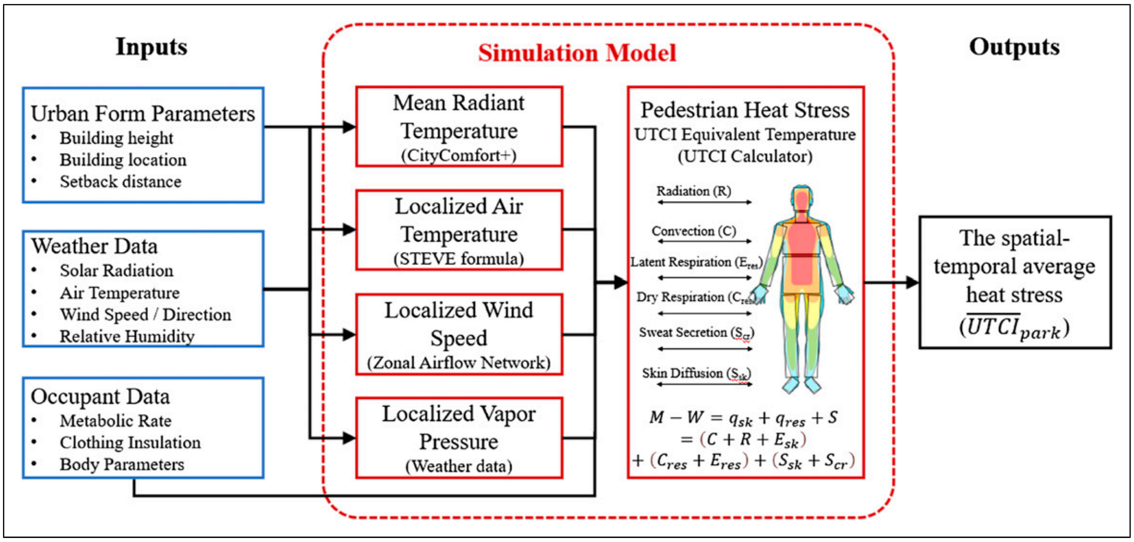

Figure 2. A conceptual framework of simulation of pedestrian heat stress in urban areas.

Table 1. The input parameters in T_{mrt} simulation.

Item	Input
Surface material	Concrete
Albedo of surface	0.35 (ratio)
Surface emissivity	0.95 (ratio)
Convective coefficient	15 (W/m^2 K)
Heat transmission coefficient (walls and the ground)	0.6 (W/m^2 K)

$$T_{max} = 7.542 + 0.684\, T_{max}^{Ref} + 0.003\, SOLAR_{max} + 0.005\, PAVE – 0.016\, HBDG + 6.777*10^{-6}\, WALL + 1.467\, SVF + 1.466\, ALB \quad (3)$$

where PAVE is the percentage of pavement area within the 50 m radius from the assessment point; HBDG is the average height to building area ratio, an indicator of the thermal massing of the surrounding built environment[42]; WALL is the total wall surface area; GnPR is the Green Plot Ratio (GnPR), originally derived by Ong[43]; SVF is the sky view factor; ALB is the average surface albedo; T_{max}^{Ref} and T_{min}^{Ref} are the daily maximum and minimum temperature from a reference weather station. SOLAR$_{max}$ is the maximum value of solar radiation of the day.

The hourly air temperature was inferred from the temperature curve. Real time predicted air temperature (T_a) at a specific hour was calculated according to equation (4), using the T_{min}, T_{max} at this point, T_{min}^{Ref}, T_{min}^{Ref} and real time air temperature (T_{hour}^{Ref}) at reference point

$$T_a = T_{max} - \frac{\left(T_{max}^{Ref} – T_{hour}^{Ref}\right) * (T_{max} - T_{min})}{T_{max}^{Ref} - T_{min}^{Ref}} \quad (4)$$

Localized wind speed was simulated using a zonal airflow network model, which estimates the flow speed at pedestrian level, 1.5 m above the ground (V_a). The zonal model offers advantage in terms of computing speed compared with a classic CFD model. It can also be easily connected with the genetic algorithm using the Python Programming Language. The zonal model has been developed and evaluated against field measurements in a mock-up street canyon site and in real urban neighbourhoods in Hong Kong.[44,45] The mode inputs are 3D urban geometries and external wind from meteorological record at a reference height. The outputs are localized air temperature, pressure and airflow patterns by solving mass, pressure and energy balance equations.

The calculation of temperature, pressure and surface thermal boundaries are introduced below. The temperature boundary at the rural boundary layer was calculated using the vertical diffusion model (VDM) developed by Bueno.[46] The VDM was based on first-principles method (vertical heat diffusion and sensible heat fluxes) and was evaluated in field studies. Assuming the lower bottom of the rural boundary layer was measured using meteorological information at an operational weather station. The conditions at height z can be solved using one-dimensional transition heat diffusion equitation.

The pressure boundary consists of both static and dynamic (wind-driven) pressure at the edge of the urban canopy layer. The static air pressure (P_a^s) at any given height can be inferred from an operational weather station after adjusting for the stacking effect due to gravity as given by equation (5)

$$P_a^s = P_a - \rho g H_z \tag{5}$$

where P_a is the measured barometric pressure under the temperature T_a at operational weather station A; ρ_a is the density of the air; H_z is the vertical elevation of the point.

The dynamic air pressure P_i^d at the windward side was calculated using equation (6)

$$P_i^d = \frac{1}{2}\rho V_p^2 \tag{6}$$

where V_p is the air velocity perpendicular to the zone surface after adjusting for vertical profile, it can be calculated using observations from an operational weather station.

Pedestrian Heat Stress (UTCI) was assessed using the equivalent temperature in Universal Thermal Climate Index (UTCI), the state-of the-art thermal comfort metrics.[47] UTCI is based on the human body energy balance and thermal regulation. As equation (7) shows, the inputs data are pedestrian level air temperature (T_a), mean radiant temperature (T_{mrt}), wind speed (T_a) and relative humidity (RH) and these were obtained from the previous steps. The outputs are human thermal stress measured in UTCI equivalent temperature

$$\mathrm{UTCI} = f(T_{mrt}, T_a, V_a, RH) \tag{7}$$

The calculation of human body energy balance and thermal regulatory response is provided in equation (8), where bodily energy gained from metabolism (M) equals the sum of external work (W), convection (C), radiation (R), skin diffusion (E_{sk}), dry respiration (C_{res}), latent respiration (E_{res}) and sweat secretion (S_{sk}). The computing of UTCI was implemented using the UTCI calculator as given by equation (8), a six-order polynomial approximation algorithm developed by Brode et al.[48]

$$M - W = q_{sk} + q_{res} + S = (C + R + E_{sk}) + (C_{res} + E_{res}) + (S_{sk} + S_{cr}) \tag{8}$$

A design generator was developed to automatically produce large numbers of design options with variations in urban form parameters, to be specified in the section 'Design Application'. The design generator, writing in Python programming language, is linked to the aforementioned simulation model to automatically generate a large database of design options and simulated cooling performances for the training of machine learning models.

Training of neural network surrogate model

A machine learning model was used to learn from the large database of design variations and simulated cooling performance. The Multi-Layer Perceptron Feedforward Neural Network (MLP)[49] was adopted in this study. MLP is a popular type of Artificial Neural Network algorithm (ANN)[30] to describe the behaviour of a non-linear system. The input layer of the MLP model is the urban form parameters and the daily summary of weather conditions; the output layer is the cooling performances measured in UTCI. Multiple hidden layers were developed with information passed between layers. The weight parameters were trained using the Back Propagation (BP) method,[50] a widely used algorithm to minimize the mean square difference of the true value and predicted value of the neural network.[51]

Model specification.

The layered structure of the MLP model is shown Figure 3. The input layer consists of a set of multiple parameterized design features, weather conditions, etc. The output layer consists of the indicator of the cooling performance $Y = (UTCI)$, which is defined as the on-site average hourly UTCI values during the assessment period. A number of hidden layers were created in-between the input and output layers. The model can be described as $\widehat{Y} = f(W, X)$, where W is the weight parameter of neurons. The MLP was implemented in the Python programming language with two software libraries, TensorFlow[52] and Keras.[53]

Model Training consists of the following steps. All parameters from the input database were normalized using a Z-score approach, in which a normalized value of $z_i = \frac{x_i - \bar{x}}{s}$ was calculated for each input x_i, where $\bar{x}$ and s were the

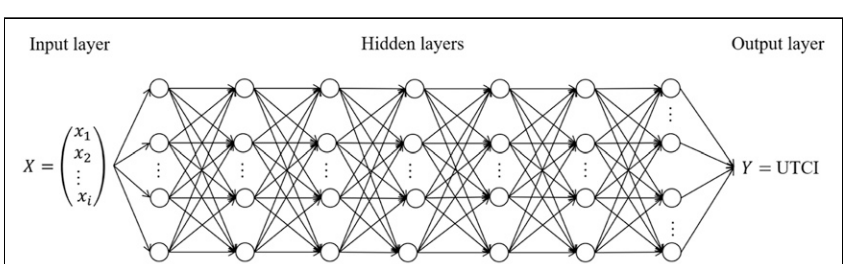

Figure 3. A conceptual diagram of the structure of the MLP model.

sample mean and standard deviation. The normalized database inputs were then split into the training set, the validation set and the testing set. The training set was provided to the nine-layer MLP, which learns the weight and threshold vector of each neuron and minimizes the error between the predicted and the target value in the training dataset. The parameters used are shown in Table 2. The training was considered complete, when the Mean Squared Error (MSE) from both the training and validation set started to increase in the validation set. Lastly, the testing set was used to assess the overall accuracy of the MLP model. The parameter tuning process including learning rate, the batch size and the epoch number was conducted to determine the MLP's parameters. The MLP was implemented in the Python programming language with Scikit-learn, a machine learning library for Python.[54]

Design optimization

The aim is to develop a neural network-enhanced design optimizer for urban cooling performance. A key challenge for design optimization is the computational load associated with frequent calls to the simulation-based objective functions. Our approach was to replace the computationally expensive simulations with the Neural Network-based Surrogate Model (NNSM), which can approximate the behaviours of the simulation model with an enhanced speed. The NNSM can then be embedded in the genetic algorithm workflow as a screening tool to filter under-performing design options, reducing the number of calls to objective functions, therefore, improving the speed of design optimization.

A design optimizer based on genetic algorithm

The genetic algorithm was used to optimize design options based on urban cooling performances. It was used to generate design options based on features of the parent generation, adhering to the principles of hybridization (cross-over) and random variation (mutation); these design options were then tested by the NNSM for their cooling performances (fitness test). High-performing design options were kept, passing their design features to the next generation of options. The above process was repeated until the performances converge, that is, no observed cooling performance improvements over a pre-defined number of generations. The inputs of GA include: (1) Design Constraints, including the Floor Area Ratio (FAR) and the physical constraints of the site and parcel boundaries, (2) Selection Criteria, the rule of survival of higher fitness value, in this case, the urban cooling performance, (3) Population Number, the number of design options in each generation, (4) Maintain Rate, the percentage of design options which can be carried over to next generation[55] and (5) Inbreeding Factor, the relative offset of mating between neither very similar nor very different individuals based on the genetic distance which was used to control the process of finding a mate. The outputs were optimized design options. The genetic algorithm was implemented using the Galapagos plugin,[20] an optimization software package. Urban design options were generated and passed into the simulation model to test their cooling performances. The above workflow was automated using a script written in Python programming language.

Cross-checking of NNSM using simulation

The optimal design option identified by the NNSM and the genetic algorithm was passed to the simulation model for cross-checking. The aim was to check whether the predictions from the machine learning models agree reasonably well with simulated data. If the agreement between the two falls within an acceptably small threshold, the optimal design was considered valid. Alternatively, the option was sent back to the genetic algorithm for further optimization. The cross-checked optimal design option was passed on to human designers for further evaluation, such as whether the blockage of views of certain buildings, or whether two nearby buildings overshadow each other.

Formulation of design principles

In addition to the optimal design option, the MLEDO approach can also yield a set of design principles, or 'the rule of thumb', to enhance users' understanding of design parameters in relation to cooling performances. Such

Table 2. Parameters of the multi-Layer perceptron feedforward neural network.

Number of input layer	Number of neurons in hidden layers: 1^{st} and 2^{nd} hidden layer	3^{rd} and 4^{th} hidden layer	5^{th} and 6^{th} hidden layer	7^{th} hidden layer	Number of output layer	Activation function
1	256	128	64	32	1	Rectified linear units (ReLu)

principles help to explain why the optimal design option performs better than others, allowing human designers to flexibly revise and further develop the final design option, taking into consideration for multiple priorities and stakeholder inputs in practice. The Random Forest Model (RFM), an ensemble learning method that operates by constructing multiple decision-trees during training,[56] was used to rank the relative importance of design parameters in their contribution of the cooling performance, that is, $\overline{UTCI}_{park}$. The structure of RFM is shown in Figure 4. The input dataset with design parameters $X = (x_1, x_2, \ldots x_{36})$ were randomly selected to construct multiple decision-trees during the training procedure; Each decision-tree lead to a predicted cooling performance $Y = (UTCI)$; the final prediction of Y was produced by taking an average for predictions from individual decision-trees. The importance of each input design parameters in relation to $\overline{UTCI}_{park}$ was determined using a difference score following the approach by Zhu et al.,[57] which was computed by averaging the difference in out-of-bag error before and after the permutation over all decision-trees, normalized by the standard deviation of these differences. Fivefold cross-validation was applied in the parameters tuning procedure to determine the best REM parameters, including the numbers of trees in the model, the maximum depth of each tree, the minimum samples used to split the tree node, etc. The RFM was implemented in the Python programming language with Scikit-learn, a machine learning library for Python.[54]

Design application

The MLEDO approach was applied in an urban site in Shenzhen, China. The objective is to evaluate the feasibility and the usefulness to design practitioners. The optimization performance of the MLEDO approach was compared with those of a conventional Simulation-based Generic Algorithm Design Optimizer (SGADO) and with the best design options from human designers.

Urban site

The MLEDO approach was tested in an urban site located in Shenzhen, China of the humid subtropical climate. The 225 × 225 m size was situated in the Guiwan Development Area in Nanshan District of Shenzhen. The development scheme includes a park at the centre (105 × 105 m), surrounded by 12 development parcels identical in size and shape (45 × 45 m) (Figure 5). The parcels are separated by roads measuring 15 m in width. The weather file was taken from the USDOE for the location of Shenzhen, China.[58] To simplify, a constant easterly wind of 1.9 m/s at the reference height of 10 m above ground[59] was used as the simulation inputs, which was based on the dominant easterly wind under the local climate. This assumption may not work for other climate types with greater variations in wind conditions.

The Objective Function is to minimize the pedestrian heat stress within the park within the assessment period during the daytime hours. The spatial-temporal average heat stress ($\overline{UTCI}_{park}$), measured in UTCI equivalent temperature was used as the performance indicator, as it is shown in equation (9)

$$\overline{UTCI}_{park} = \frac{1}{S}\sum_{s=1}^{s=S}\left(\frac{1}{D}\sum_{d=1}^{d=D}\left(\frac{1}{H}\sum_{hr=start}^{hr=end} UTCI_{s,d,hr}\right)\right) \quad (9)$$

where s is a particular point within a total of S points inside the park; d is the d^{th} day a total of D days during the

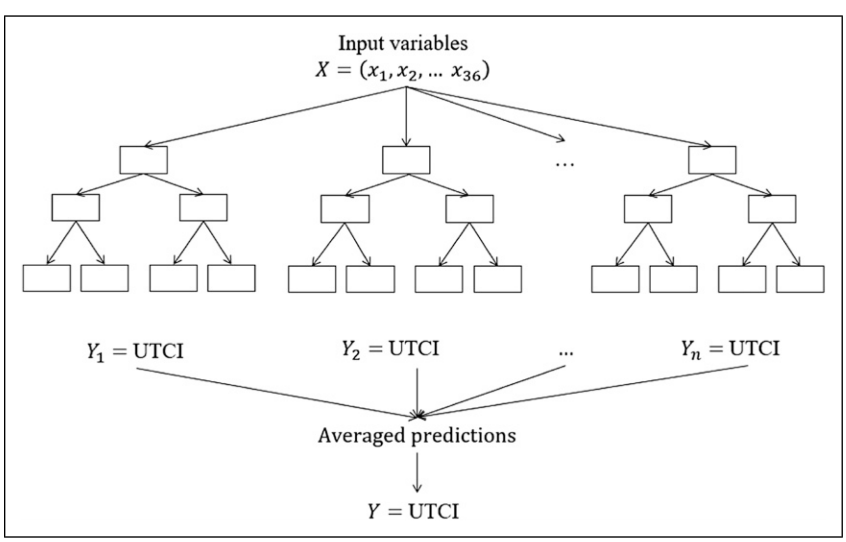

Figure 4. A conceptual diagram of the structure of the Random Forest Model (RFM).

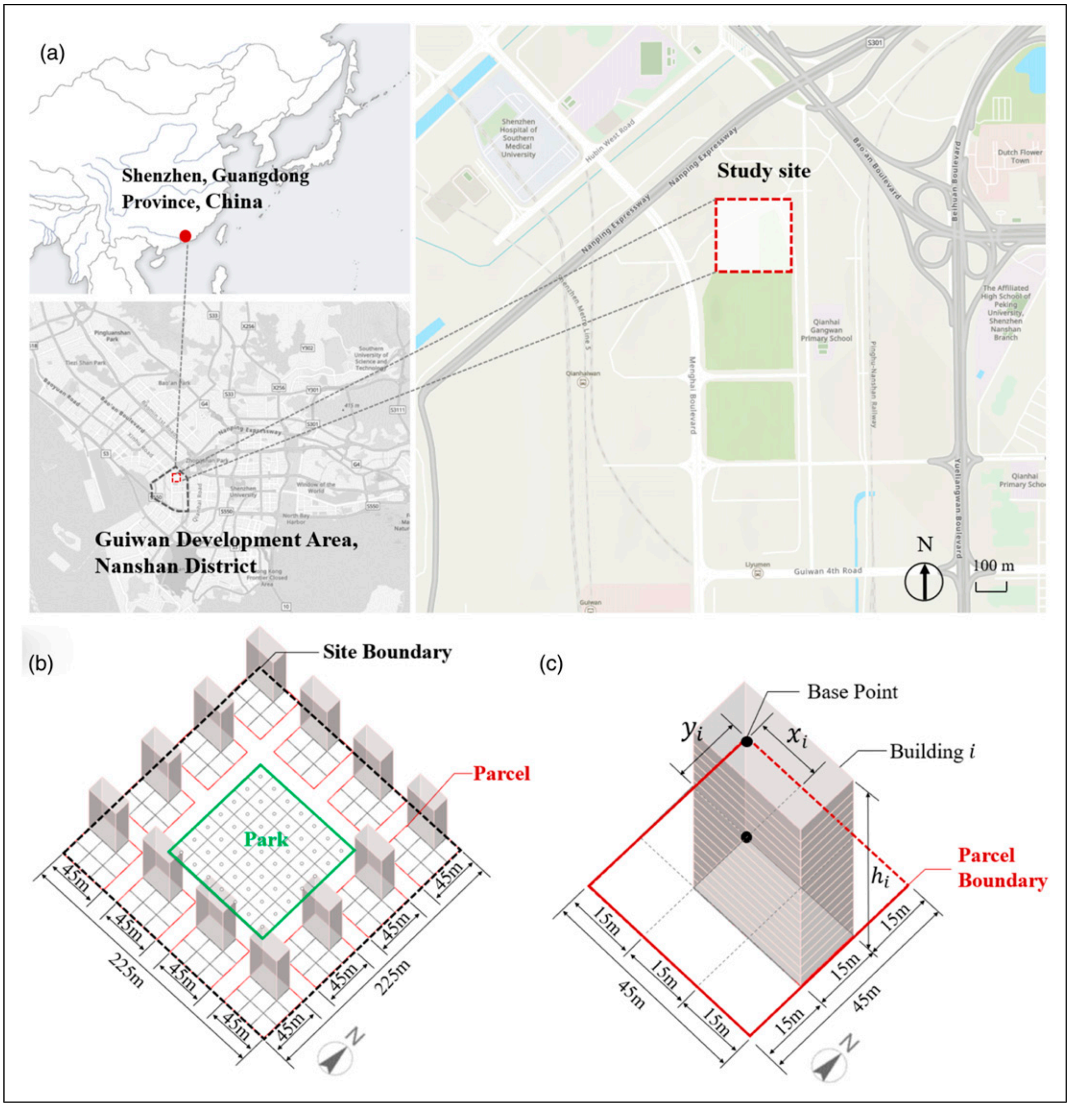

Figure 5. (a) The location and context of the urban site in Shenzhen, China; (b) the layout of the urban site with parcels and park; (c) urban form parameters at each parcel, including building offset from base point (x_i, y_i) and height (h_i).

assessment period, in this case, 184 days between 1 May and 31 October; *hr* is a particular hour between the start and the end of a period of *H* hours, in this case, between 10:00 and 17:00. The objective function was set to minimize $\overline{UTCI}_{park}$, which can be expressed as a function of urban form parameters x_i, y_i, h_i for a total of 12 parcels, as it is shown in equation (10)

$$\text{Minimize}\{f(x_i, y_i, h_i), 1 \le i \le 12\} \quad (10)$$

The MLEDO was tested for two optimization tasks based on two different objective functions: the first is the temperate-day optimization, to minimize $\overline{UTCI}_{park}$ between 10:00 and 17:00 on 29 October, the temperate day which is representative of the annual average conditions of the local climate. The second is the hot-season optimization, to minimize ($\overline{UTCI}_{park}$) between 10:00 and 17:00 for a period of the entire hot season (184 days), a period of significant heat stress and of practical concern for urban designers.

Design Constraints were made for building height and location, mimicking the contemporary development pattern found in Southern China. The Floor-Area ratio (FAR), the ratio between total building floor area and the overall site area, was fixed at 3.2. Only one building was allowed in each parcel, which occupied a fixed footprint area of 30 × 15 m. The longer side of the building was set to face south, in reference to the solar access restriction and market preference for residential buildings in Chinese cities**.** To simplify, a building was located within the parcel boundary, discretely on the 15 m grid (Figure 5(b)). The building height can vary between 25 and 35 floors, or 75 and 105 m based on a standard floor to floor height of 3 m.

Urban form parameterization. The location and height of buildings can vary by design. Each design option can be described by 36 parameters, as it is summarized in Table 3 and (Figure 5(b)). Three parameters were used to describe each parcel i, including building height (h_i) and offset distance from the basepoint in X (x_i) and Y axis (y_i), and 36 parameters for a total of 12 parcels (Figure 5(a)).

Design generation. Design options in terms of 3-dimentional building forms were generated randomly using the Grasshopper software[60] within the Rhinoceros 5.0 platform.[61] The design generator produces random combinations of the 36 urban form parameters. Design options in violation of the design constraints are discarded by a penalty function written in the Python programming language. The convergence criteria were set identically for both MLEDO and SCADO: The genetic algorithm would converge if there are no improvements observed in cooling performances over the last 50 individual design options.

Comparison with human designer options

A group of human designers, in this case, 26 graduate students at the master's level from the authors' institution participated in the study. They were of the background in urban planning, urban design and architecture, and they were divided into 8 groups to participate in a design game in a classroom setting to compete for the best design option for urban cooling performance. The participants were asked to follow the identical objectives and design constraints as those specified above. They need to follow the rules on Floor Area Ratio, building height, etc. The winning criteria were to minimize the spatial-temporal average heat stress $(\overline{UTCI}_{park})$ on the temperate day (between 10:00 and 17:00 on 29 October).

Each group was expected to complete two rounds of design excises within 2 h. They were provided with the simulation model in the format of CityComfort+,[14] a software plugin in Rhinoceros with a graphical user interface which can be used to simulate the on-site mean radiant temperature and localized temperature using the STEVE formula and pedestrian heat stress in UTCI equivalent temperature. The students were also provided with the FlowDesigner 10.0,[62] a CFD simulation software which can simulate the on-site localized wind speed at pedestrian height. Students have learned to use the two software previously. The best design options from the human designer were compared with the MLEDO optimal and those of the SGADO in terms of urban cooling performances.

Results

The neural network surrogate model was trained and cross-checked using simulated dataset. The optimization performance of the MLEDO was compared with those of the SGADO and then checked with the best-performing options from human designers. The usefulness and limitation of the MLEDO tool in early-stage design were discussed.

Data characteristics

A database consisted of 13,818 design options and their simulated cooling performance was obtained. The assessment period was chosen strategically since an exhaustive hourly simulation for the 13,818 design options between 1 May and 31 October (184 days, 1472 h) would take more than 3 million simulation runs, which is computationally challenging. To reduce the calculation load, four representative days were chosen to simulate large numbers of design options: 31 May, 1 July, 12 August and 29 October, which feature daily average temperature close to, therefore representing, the typical summer day, the hottest day, a warm day and a temperate day. To ensure the simulated database cover the weather variations in each month, simulations were also performed for the entire month of June, July and September for a medium-performing design option, each last 30 days or 720 h. The above choice of simulation period allows for a complete coverage of weather conditions throughout the hot season while reducing the calculation load (Table 4).

Table 3. Descriptions of the urban form parameters.

Urban form parameters (unit)	Description	Data type (range)
Building offset (m)	x_i = offset distance from base point in X axis	Discrete (0, 15)
	y_i = offset distance from base point in Y axis	Discrete (0, 15, 30)
Building height (m)	h_i = building height	Continuous (75–105)

Table 4. The choice of simulation period to ensure all weather conditions are covered while reducing the calculation load.

Date (length)	31 May (1 day)	1–30 June (30 days)	1 July (1 day)	2–31 July (30 days)	12 August (1 day)	1–30 September. (1 day)	29 October (1 day)
Mean hourly air temperature (°C)	27.6	28.3	32.8	28.9	28.5	27.9	24.2
Mean hourly relative humidity (%)	71.9	80.7	61.5	74.8	77.3	75.3	59
Mean hourly direct normal radiation (W/m^2)	145	190	669	317	445	255	336
Representation	Warm day	Hot month	Hottest day	Hot month	Typical summer day	Warm month	Temperate day
# of design options simulated	2244	1	2018	1	2087	1	2189

Both the MLEDO and SGADO were used to conduct the temperate-day optimization, to minimize $(\overline{UTCI_{park}})$ between 10:00 and 17:00 on 29 October. Both results were compared the best-performing design options from human designers. The MLEDO was also used to conduct the hot-season optimization, to minimize $(\overline{UTCI_{park}})$ between 10:00 and 17:00 for a period of the entire hot season (184 days), which is a computationally challenging task for SGADO.

A total of 15 design options were received from 8 groups of human designers. The design deliverables include 3D urban design options in Rhinoceros file format and simulated cooling performances between 10:00 and 17:00 on 29 October. For verification, the cooling performances of these design options were independently assessed by a researcher proficient with simulation software. The results were compared with those from the MLEDO and SGADO.

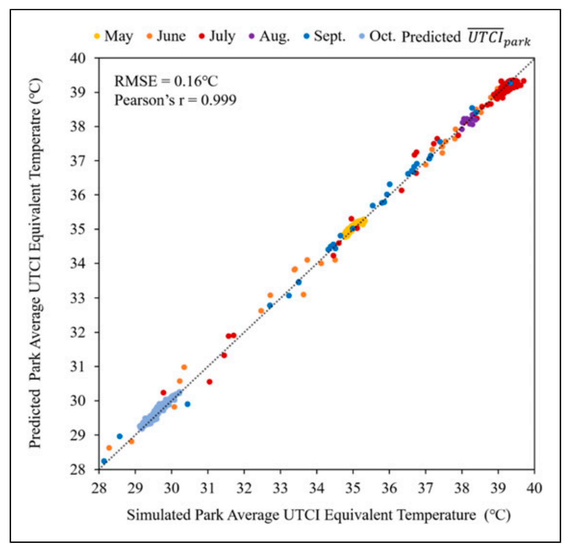

Figure 6. Predicted cooling performances $(\overline{UTCI_{park}})$ by the Neural Network Surrogate Model versus the simulated values. Each point represents an average value assessed for the daytime period (10:00–17:00) on a particular day during the hot season.

Evaluation of the performance of the neural network surrogate model

The Neural Network Surrogate Model (NNSM) can predict the simulated cooling performances of various design options. The NNSM was trained using the input database of 13,818 design options, consisting of 36 urban form parameters and simulated cooling performances measured in the park average UTCI $(\overline{UTCI_{park}})$. The dataset also comprises the date of the year (day1 = 1 January., Day 365 = 31 December.) and five weather parameters, that is, the daytime hour (10:00–17:00) mean air temperature, mean relative humidity, mean solar radiation, the maximum solar altitude and mean sky cover. A randomly selected subset of 11,054 design options (80% of the total) was used for model training. The remaining 20% of the design options were used to evaluate the model performance in predicting $\overline{UTCI_{park}}$. Results are shown in Figure 6. The NNSM-predicted $\overline{UTCI_{park}}$ agrees reasonably well with simulated value, with the Pearson's correlation coefficient of 0.998 and the Root Mean Square Error (RMSE) of 0.16°C, which is below the labelled accuracy range of 0.2°C of many temperature sensors, such as the onset temperature and RH sensor (U23 Pro V2).

Results of the NNSM were evaluated using the simulation model for the weather condition on 12 August and 29

October. Satisfactory agreements were observed between the two, with a difference smaller than 0.02°C in $\overline{UTCI}_{park}$ (Table 5) on both days. Results for the hot-season optimization have not been evaluated in this study since the simulation run for an excessively long period is computationally infeasible.

Human designer results

Considerable variations were observed among the design options by human designers in terms of simulated cooling performances. The range of simulated $\overline{UTCI}_{park}$ by the 8 groups is between 29.3 and 31.1°C (Figure 7). The performance gap among groups can be explained by background knowledge and simulation skills. Members from high-performing groups, such as groups 3 and 6, possessed good knowledge in sustainable design, proficiencies in simulation and often with years of professional experiences. In comparison, members of group 4 lacked background knowledge and simulation skills. A technical error in simulation disrupted their workflow and misled their decision-making, leading to a low-performing round 1 result and no time for the second round. Our observation is consistent with previous studies that software proficiencies influence the performance of design outcomes.[63]

The performance improvements between the two rounds were insignificant. While half of the groups (group 3, 5, 6) saw the cooling performance of their design options improved between round 1 and 2, the other half (group 1, 2, 8) saw no improvements. Group 4 did not complete round 2 design within the time limit. Although designers were given simulation tools such as CityComfort+ and CFD, simulated results did not automatically translate into design decisions. Such gap is often replaced by 'guestimate', while improvement in design performance is not always guaranteed.

Options from human designers were often found to 'break the rules', or creative urban design or architectural strategies beyond the design parameterization adopted on the urban site. An example is the design option proposed by group 6 in round 2, which featured shading canopies, elevated building ground floor, and permeable building massing to facilitate wind (Figure 9(c)). While these design features can effectively increase cooling performances, including these features as design parameters in MLEDO would inevitably increase the calculation load and possibly reduce its optimization performance. The hybrid approach, a machine learning-enhanced optimization tool in combination with human inputs, can serve as an effective solution.

Table 5. Cross-checking of the cooling performance ($\overline{UTCI}_{park}$) of the optimal design option identified by the machine Learning-Enhanced design optimizer.

Date	Prediction, °C	Simulation, °C	Difference
12 Aug.	37.88	37.91	0.02°C
29 Oct.	28.99	28.99	<0.01°C

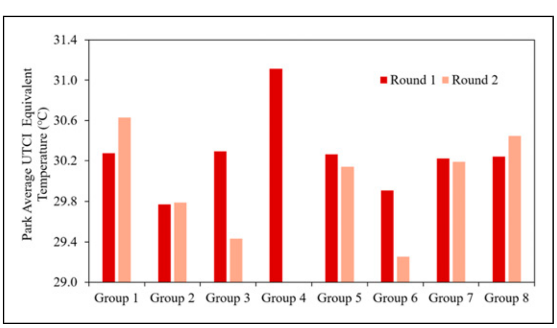

Figure 7. Simulated urban cooling performances of best options by human designers in two rounds of design game.

Comparison of optimization performances with and without machine learning

The MLEDO approach was compared with SGADO in terms of the optimization process, computational speed and the performance of optimal design options.

Optimization process

Both the MLEDO and SGADO exhibited satisfactory convergence towards better cooling performance from generation to generation, although the performance of individual design options tends to fluctuate and occasionally deviates from improvements. A comparison between MLEDO and SGADO for the temperate-day optimization is shown in Figure 8. The SGADO converged at a local optimal ($\overline{UTCI}_{park}$ = 29.2°C) at the 15th generation since no performance in the last 50 individual design options. The MLEDO did not converge until reaching the 33rd generation, at a better-performing design option ($\overline{UTCI}_{park}$ = 29.0°C). The cooling performance gap among various design options can measure up to 1.2°C in $\overline{UTCI}_{park}$, suggesting that the design of the building layout could significantly affect urban cooling performances.

Computational speed

The MLEDO enjoys an advantage for a long-period assessment over SGADO. The latter requires extensive calls to the objective function that is practically infeasible. However, MLEDO was outperformed by SGADO for a short-period assessment since the latter requires no training of neural network model. An example was provided for the long-period assessment (the hot-season between May and October) as shown in Table 6. The MLEDO took 102 h (4+ days) to finish using a GPU-accelerated desktop computer (Intel Processor i7-7700 CPU @ 3.60 GHz, 32 GB RAM, Nvidia GeForce RTX 3070, 8 GB), which was some 40 times faster than SGADO. MLEDO's speed allows users to set more stringent convergence criteria in the genetic algorithm, which can elevate its optimization performance. For the short-period assessment (Single-Day) as shown in Table 7, MLEDO took twice as much time as SGADO to complete the calculation, and the majority of its computational time was spent on model training, while SGADO runs faster since it requires no training. However, the MLEDO ran twice as fast as the SGADO, measured using the time needed per design option. It suggests that MLEDO out-competed the existing approach of SGADO in replacing time-consuming simulation.

Optimization results

Improved cooling performance. The MLEDO approach can identify optimal design options with better cooling performances compared with those of the SGADO. A comparison between the former and the latter is shown in Figure 9(a) and (b), with the best design options by human designers as shown in Figure 9(c) in reference. The objective functions were set to minimize the $\overline{UTCI}_{park}$ on the temperate day (29 October). Results from the MLEDO optimal have outperformed the SGADO by 0.2°C, which is

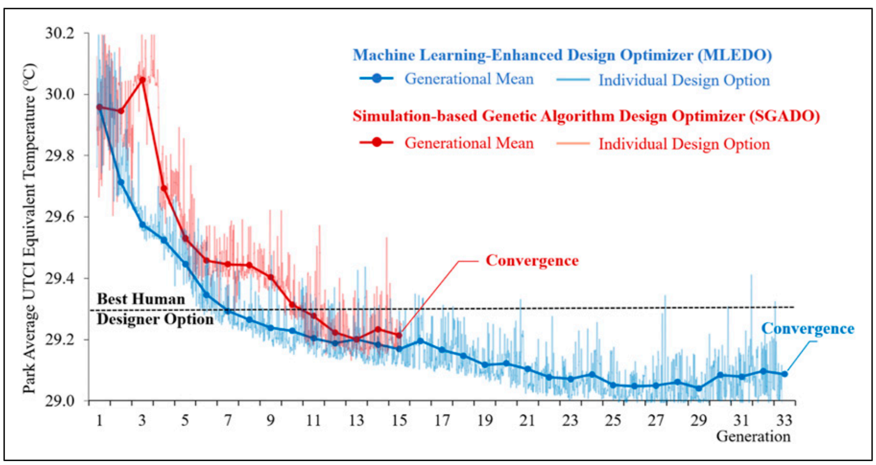

Figure 8. Optimization process of minimizing pedestrian heat stress by Machine-Learning-Enhanced design optimizer.

Table 6. Comparison of computing time between MLEDO and SGADO for hot-season assessment, using a GPU-accelerated desktop computer (Intel Processor i7-7700 CPU @ 3.60 GHz, 32 GB RAM, Nvidia GeForce RTX 3070, 8 GB).

Design oOptimizer	Data preparation	Design optimization	Total
Simulation-based Genetic Algorithm Design Optimizer (SGADO)[a]	0	4,176 h	4,176 hrs (6 months)
Machine Learning-Enhanced Design Optimizer (MLEDO)	71 h	31 h	102 h (4 days)

[a]The computing time by SGADO was estimated based on data from Table 7.

Table 7. Comparison of computing time between MLEDO and SGADO for the single-day assessment, using a GPU-accelerated desktop computer (Intel Processor i7-7700 CPU @ 3.60 GHz, 32 GB RAM, Nvidia GeForce RTX 3070, 8 GB).

Design optimizer	Data preparation	Design optimization	Total
Simulation-based Genetic Algorithm Design Optimizer (SGADO)	0	17 h	17 h
Machine Learning-Enhanced Design Optimizer (MLEDO)	17 h	19 h	36 h

a notable reduction in the spatial-temporal average heat stress within the one-hectare park. Both MLEDO and SGADO are better than those from human designers.

Discussion

The MLEDO workflow developed in this study is a promising tool to enhance the integrate of computational tools in design decision-making in several aspects:

First, the MLEDO approach can drive design development towards the optimal option, thus relieving human designers from guesswork or trial-and-error. Computer algorithms can achieve fast iteration in design revision, compared with the slow process for human designers: the two rounds of design exercise took 2 hours in the design game, while the average iteration for computer algorithm is 30 s on a GPU-accelerated desktop computer, or 9 min on an ordinary desktop computer. A related benefit for MLEDO is its expanded computational capacity, allowing it to identify the design optimal for the hot-season optimization (Figure 10(a)), a computationally challenging task for SGADO. The optimal design options from MLEDO outperformed those

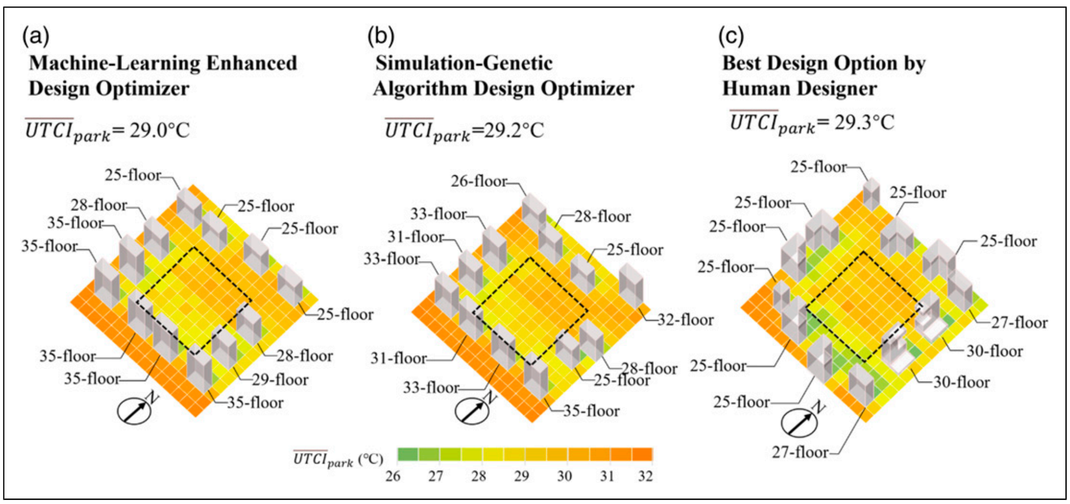

Figure 9. (a) The best design option by Machine Learning-Enhanced Design optimizer; (b) optimal design by simulation-Genetic algorithm design optimizer; (c) the best design option by human designer. The objective functions were set to minimize the $\overline{UTCI}_{park}$ on the temperate day (29 October).

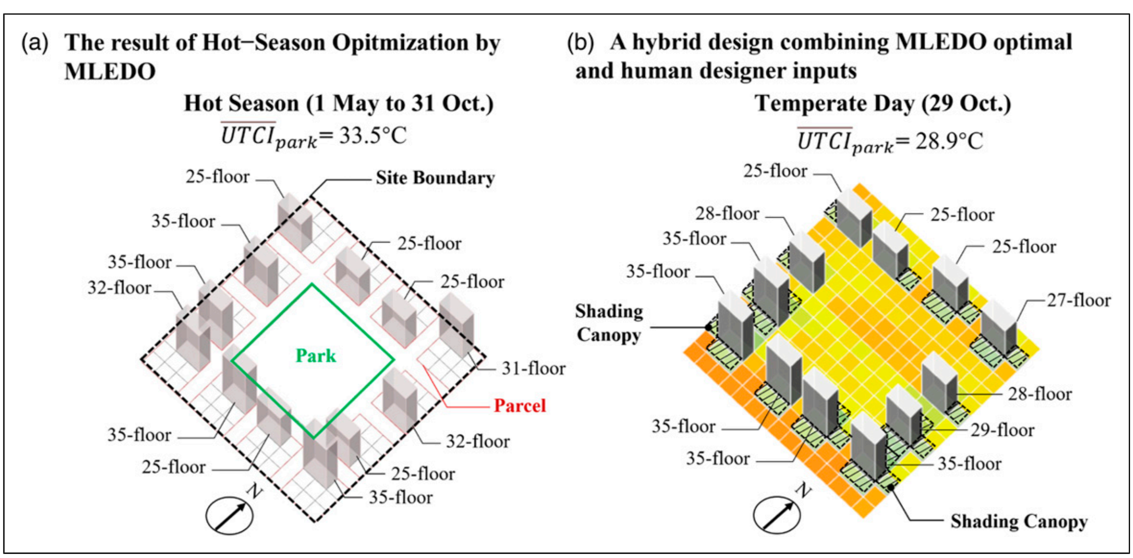

Figure 10. (a) The design optimal from the hot-season optimization by MLEDO (b) a hybrid design option combining the urban form parameters of MLEDO optimal and human designer inputs on shading and elevated building ground floor.

from the SGADO and human designers. This is especially useful for those designers who are less experienced in sustainable design and simulation models.

Second, the MLEDO is especially useful for early-stage design decision-making. It relies on human inputs on design constraints and objective functions, while it can arrive at the first point of early design option towards the final design. The MLEDO approach is expected to be more efficient during the early-stage design, when the urban form parameters and constraints are less complex. An example is provided in Figure 10(b), in which a human designer can take over the urban design option and further develop necessary details, such as alter the shape of buildings for architectural reasons, add shading devices, landscape features such as trees and lawns, which can effectively reduce the $\overline{UTCI}_{park}$ on 29 October further to 28.9°C. The improvement has practical significance since the value is close to the thermal acceptance range identified for the humid subtropical climate.[4] The hybrid solution combining the optimization and human designer inputs is expected to bring the MLEDO approach one step closer to practical use.

Lastly, the MLEDO approach can generate a set of design principles or ‘rule of thumb’, allowing human designers to further revise/develop the final design. This gives the MLEDO approach an edge over the prescriptive, inflexible approach of a conventional optimization programme. The latter gives an explicitly computer-generated optimal design option without justification, which is difficult to be implemented as-it-is in practice. An example is shown in Figure 11, in which the design parameters were measured and ranked in terms of their contribution to the cooling performances, using RFM for the input database, consisting of 2189 design options and simulated cooling performances on 29 October. The top 15 most important design parameters were categorized by a researcher into three design principles: (1) buildings to the west of the park (parcel 5, 7, 9) should be aligned close to the park, to provide shading from the afternoon sun; (2) buildings to the south of the park (parcel, 9, 10, 11 and 12) should be as tall as possible in order to provide shading from sunlight. (3) Buildings from both the south and north side of the park should be aligned to form a continuous breezeway, in order to enhance wind.

As a first step towards a machine learning-enhanced design tool, this study exhibits several limitations. First, the current NNSM model is not expected to be applicable to alternative site layouts or a different climate zone. New training datasets are needed each time, should the site/climate condition change. This is a limiting factor for adopting the MLEDO approach in real-world projects. Second, the MLEDO takes some 4 days of computing time for the hot-season optimization. While this is an achievement compared with 6 months for the SGADO, this is still beyond what a real-world project can accept. Further studies can extend the design and weather conditions to enhance the generalizability of the ready trained model, which can save the majority of the time spent on the preparation of training data. Third, a site averaged value was used to represent on-site heat stress and the current NNSM model is limited in predicting thermal matrix, which indicates the proposed method was not capable to investigate the spatial and temporal distribution of heat stress for the achieved optimal design. In addition, the vegetation was not considered in assessing thermal comfort although it has a significant impact on mitigating heat stress. Further studies can include greenery to improve the reliability of the model.

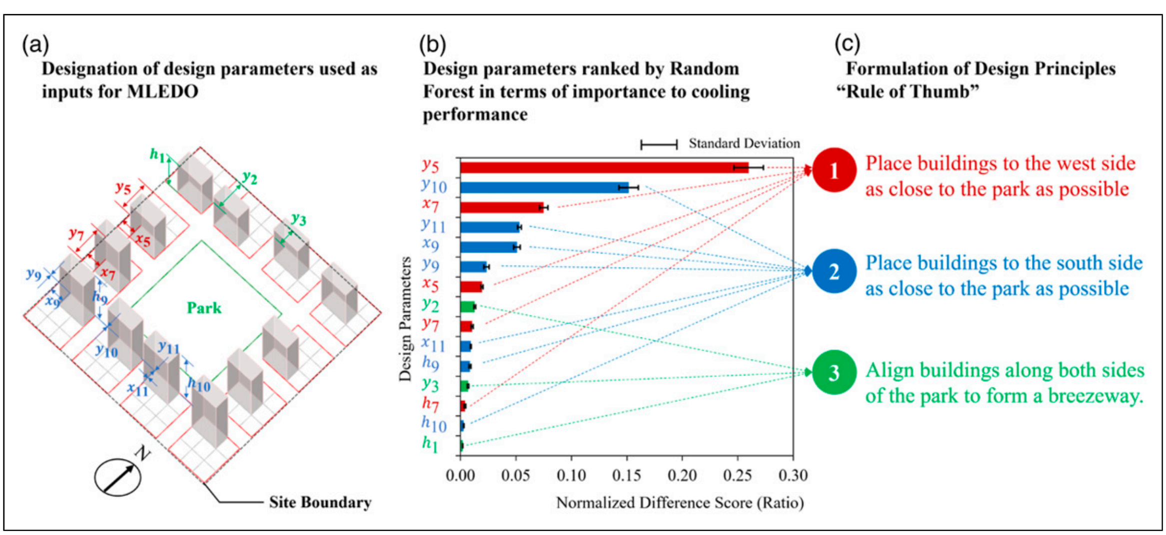

Figure 11. Measurement of the importance of design parameters using the random forest model (RFM) and the formulation of design principles or ‘rule of thumb’.

Conclusions

This paper describes the development of the Machine Learning-Enhanced Design Optimizer (MLEDO), a computerized tool to automatically identify optimal design options in cooling performances. The novelty of this research lies in the use of neural network models for fast prediction, which is linked to a genetic algorithm to identify optimal design options. MLEDO was tested in a new development urban site in Shenzhen, China. Results were compared with those of a traditional Simulation-based Genetic Algorithm Design Optimizer (SGADO) and best-performing design options from human designers. The major advantages of the MLEDO lies in three areas. Firstly, the MLEDO algorithm can automatically identify urban design options which outperform those of the traditional simulation-based genetic algorithm and human designers by 0.2°C and 0.3°C, respectively, in simulated cooling performances. Moreover, it expands computational capacity in handling prolonged assessment period, which was some 40 times faster than SGADO for the hot season (between May and October) assessment. At last, it can also provide a set of design principles to enhance user understanding as to why an optimal option performs better, allowing flexible revisions and further development of the final design. MLEDO has the potential to be further developed into a supporting tool for the early design stage, which can enhance the integration of digital tools in the design decision-making process.

Statements on Author Contribution

TH contributed to optimization, simulation, analysis, figures, data curation and manuscript editing. JH contributed to the conception, study design, first draft and figures. XH developed the machine learning model. LL contributed to conception and supervision. PJ contributed to manuscript revision and proof reading. All authors have read and approved the submitted version.

Declaration of Conflicting Interests

The author(s) declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

The Multi-Layer Perceptron Feedforward Neural Network (MLP) was adopted in this study. Ten MLPs were trained with different selected feature inputs in the model-built process. Model 10, which achieved the minimum RMSE in evaluation compared with alternatives, was selected as the Neural Network-based Surrogate Model (NNSM) to replace the simulations in further optimization steps.

The feature set X consisted of two sub-sets in two categories, $X_1 = \{x_1, x_2, \cdots, x_{36}\}$ contains 36 parameterized design features and $X_2 = \{x_{DT}, x_{AT}, x_{RH}, x_{SR}, x_{SA}, x_{SC}\}$

Table A1. Comparison of the performance with different NNSMs (hot-season period).

Model	Selected features in X_2	RMSE (testing dataset, $\overline{\mathrm{UTCI}}_{park}$ °C)	Pearson's r (testing dataset)
Model 1	$x_{DT}, x_{AT}, x_{RH}, x_{SR}, x_{SA}, x_{SC}$	0.16	0.999
Model 2	$x_{DT}, x_{AT}, x_{RH}, x_{SR}, x_{SA}$	0.18	0.999
Model 3	$x_{DT}, x_{AT}, x_{RH}, x_{SR}$	0.20	0.998
Model 4	x_{DT}, x_{AT}, x_{RH}	0.30	0.997
Model 5	x_{AT}, x_{RH}	0.51	0.991
Model 6	x_{DT}, x_{AT}	0.36	0.995
Model 7	x_{DT}	1.56	0.899
Model 8	x_{AT}	0.53	0.989
Model 9	x_{RH}	1.09	0.952
Model 10	x_{SR}	0.79	0.976

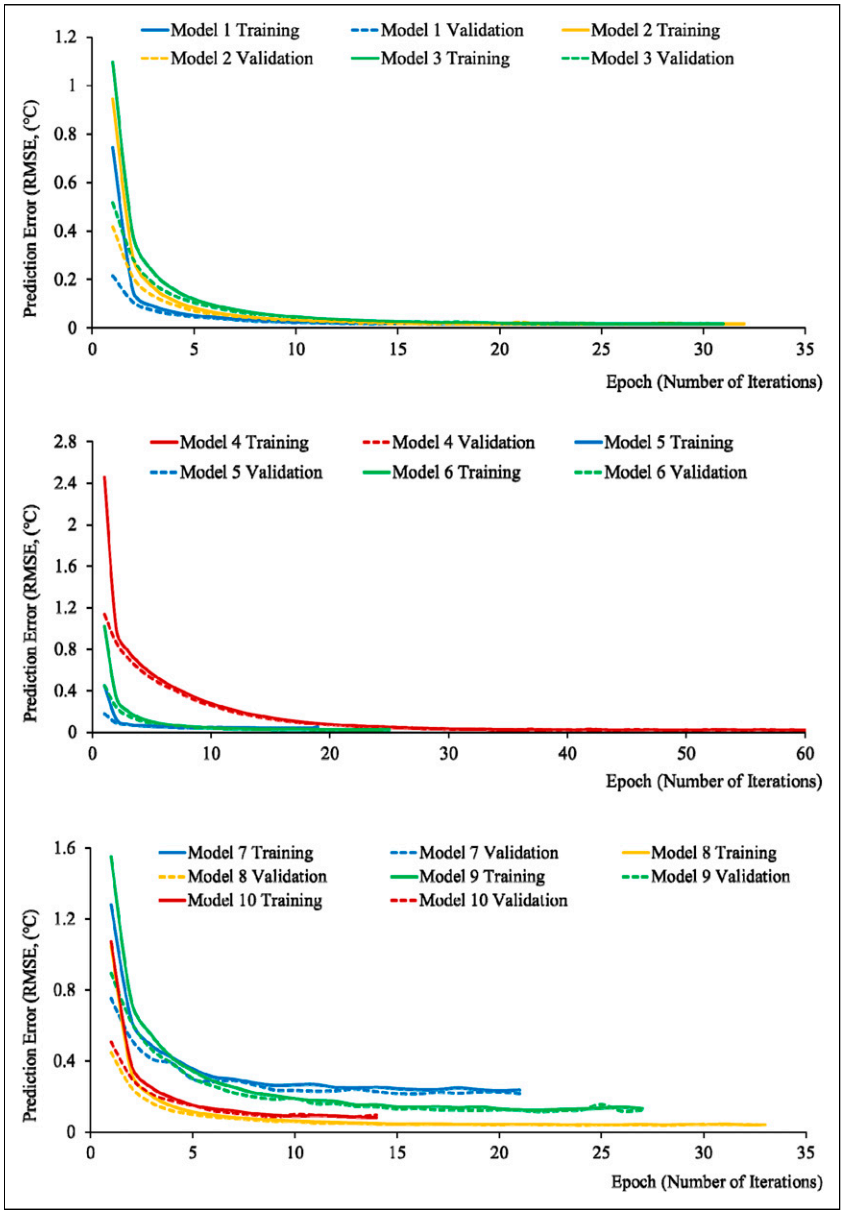

Figure A1. Learning curves of different models.

contained six features indicating the day in a year and the climatic conditions, the dates (x_{DT}, day1= 1 January, Day 365 = 31 December), the daytime hour (10:00–17:00) mean air temperature (x_{AT}), mean relative humidity (x_{RH}), mean solar radiation (x_{SR}), the maximum solar altitude (x_{SA}), and mean sky cover (x_{SC}). X_2 was built based on domain knowledge that the climatic conditions play a key role in determining the outdoor thermal environment, which is necessary to be considered in predicting the cooling performance $Y = (UTCI)$ for a prolonged assessment period covering various weather conditions. The X_2 was calculated based on the weather file taken from the USDOE.[58] In establishing MLPs, it is hypothesized that including variables representing the climatic conditions can improve the model's predictive performance. In this study, ten NNSM models were trained by combing X_1 and selecting features in X_2 as input feature set X'. The dataset $D = (X', Y')$ was split into the training set, the validation set and the testing set. An early stopping technique was adopted to avoid overfitting, which the model was evaluated on the validation after each epoch and stopped training once an increase of the RMSE, the generalization error was observed on the validation set. As shown in Figure A1, the RMSE on the training and validation set were decreased along epochs of different tested models. Table A1 shows the comparison of the performance of different models in the testing dataset and variables used from X_2. The results show that Model 1 $(X = X_1 \cap X_2)$ obtained minimum RMSE on the testing dataset with the best generalizability, the predicted results are in a good agreement with the observed value. Thus, Model 1 was chosen as the surrogate model for application in design optimization.