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Characterising the Impact of HVAC Design Variables on Building Energy Performance, Using a Global Sensitivity Analysis Framework

Maria-Anna Chatzopoulou^{#1}, James Keirstead^{*2}, David Fisk^{*3}, Christos, N. Markides^{#4}

[#]*Clean Energy Processes (CEP) Laboratory, Department of Chemical Engineering, Imperial College London, South Kensington Campus, London SW7 2AZ, UK*

¹maria-anna.chatzopoulou11@imperial.ac.uk

⁴c.markides@imperial.ac.uk

^{*}*Department of Civil and Environmental Engineering, Imperial College London, South Kensington Campus, London SW7 2AZ, UK*

²j.keirstead@imperial.ac.uk

³d.fisk@imperial.ac.uk

Abstract

Buildings are key contributors to worldwide energy consumption and emissions. In the UK, approximately 50% of the energy consumption in non-domestic buildings arises from the use of Heating Ventilation and Air-Conditioning (HVAC) systems. Even so, the selection of HVAC systems is often performed in the early design stages, when little is known regarding the system operation. Global Sensitivity Analysis (GSA) can effectively quantify this uncertainty, by identifying the most influential variables related to HVAC performance, and focusing the system design on these fewer, but most significant parameters. The present study deploys GSA instead of the simpler SA methods used in more efforts, while focusing on the parameters affecting HVAC system design. The proposed GSA framework is illustrated through an office building case-study. The performance of the heat pump and of the heat-recovery unit are identified as the most influential parameters on the system's overall energy consumption. In contrast, parameters, such as the fan-coil-unit pressure drop, and the fan efficiency, are found to have little influence on the system consumption. The analysis also provides load probability distribution curves, which can be used by decision makers to select the HVAC system that meets the design objectives, with a specified confidence level. The results reveal that the heat pump system sized at 80% of the maximum peak load estimate is capable of meeting the time-varying load of every single hour with 95% probability. Therefore, this study gives confidence that GSA can uncover the most influential parameters, and their impact in the early stages of HVAC design, based on which further system optimisation can be performed.

Keywords - *Global sensitivity analysis; Energy efficiency; HVAC*

1. Introduction

With environmental impacts and resource security putting significant stresses on a wide range of sectors, the EU have set targets for reducing the carbon emissions to 80-95% of 1990 levels, by 2050 [1]. In this context, the built environment has been identified as a key sector with high decarbonisation potential, since it is responsible for 40% of the final energy consumption in the EU, and 38% of the total carbon emissions

[2]. More precisely, non-domestic buildings are highly energy intensive, with approximately half of their energy consumption being attributed to the Heating Ventilation and Air-Conditioning (HVAC) systems [3, 4]. Consequently, to achieve energy consumption and carbon emissions reduction in the sector, it is important to evaluate the potential of integrating efficient HVAC technologies effectively.

A wide range of technologies and designs are available, resulting in a broad design solutions space. Additionally, HVAC components are selected and sized, usually in early design stages, when there is high uncertainty related to characteristics of the system [4-6]. For the system initial selection and sizing, designers use standardised methods, provided in design guidelines and, published by organisations, such as the American Society of Heating Refrigeration and Air-Conditioning Engineers (ASHRAE) [7], or the Chartered Institution of Building Services Engineers (CIBSE) [3,8]. To compensate for the inevitable uncertainty, due to lack of detailed input data, safety factors are then applied to ensure the system capacity is capable of meeting the peak load [9]. However, these practices can have a negative impact on system performance, leading to oversized equipment and, thus, part-load load operation with low efficiency.

A means of mitigating the early design-stage uncertainty is the use of sensitivity analysis (SA). SA can attribute the model output variability to each of the model input parameters, identifying the variables that are key for optimising the HVAC system performance. In this context, this study aims to develop and propose a GSA framework suitable for informing energy-technology design decisions, at the early design stages, focusing on energy-intensive buildings. Having identified the influential variables on the HVAC system performance, optimisation studies can follow, concentrating on these fewer but important parameters. This paper is structured as follows; first, the available SA techniques are introduced, and the state-of-the-art in SA applications in building energy systems is critically reviewed. Next, the GSA methods selected for the current study are presented, together with the office building case-study examined. Then, the analyses results are presented and discussed. Finally, conclusions are drawn, followed by recommendations for future research.

2. Background and Literature Review

2.1 Sensitivity Analysis Methods Overview

There are two major SA categories; the local SA methods, also called the One-at-a-Time (OAT) SA, and the global SA (GSA) methods. Local SA evaluates the change of the model output by varying only one input parameter at a time, while the remaining model parameters are fixed to one constant value (*ceteris paribus*). The advantages of this technique include its simplicity, and the fact that it is relatively quick, in comparison to GSA methods. Nevertheless, local SA is useful only for linear models, it cannot evaluate potential interactions among the input variables, as well as, it cannot quantify the contribution of each individual input variable to the model output variability [10].

In contrast, GSA methods can offer to the researcher insight to the individual model variables impact on the output variability. The inputs can be then ranked in order of significance, based on their contribution. The difference between GSA and local methods lies on the fact that the former evaluate the model around a starting baseline, whereas the GSA techniques explore the whole inputs space, while varying all variables simultaneously. GSA methods can be classified into three categories, as follows:

Regression SA: The method is based on the calculation of a number of regression coefficients. It has low computational requirements (relatively fast method), however, it is mainly suitable for linear models or models without correlated inputs.

Screening-based analysis: The screening-based analysis is commonly used to perform the so-called *Factor Fixing setting*. In this SA setting, the least influential model input parameters are to be identified, in order to reduce the model order of complexity. A significant advantage of the method is that it can handle a relatively large number of design parameters, while keeping the number of iterations required low (low computational costs). The Elementary Effects (EE) or Morris method [11] is the most well established screening method, in the field of buildings energy performance studies. The EE method is independent of assumptions related to model linearity, or of input variables correlation [12].

Variance-based SA: Variance-based methods identify the model input parameters with the highest impact on the output of interest. This SA setting is also called the *Factor Prioritisation setting*. The key added value of the variance-based methods is that i) they can estimate the contribution of each input parameters to the model outcome variability; and ii) they can evaluate interaction effects among the inputs. Nevertheless, this is accomplished at high computational costs i.e. high number of model iterations. In this category of methods, the most well established ones are the Fourier Amplitude Sensitivity Test (FAST) [13], and the Sobol technique [14, 15]. Both SAs are independent of the model form, therefore they are suitable for non-linear, non-monotonic models, or models with correlated input [16]. The interested reader can look for the technical and mathematical details of the aforementioned methods, in [10, 11, 17].

2.2 Sensitivity Analysis in Buildings Energy Performance Studies

The review findings reveal that the vast majority of the studies undertaken are focusing on building form, fabric and internal gains analysis, using fully developed thermal models [9, 18-26]. In contrast, the investigation of HVAC systems design parameters is less documented [12, 18, 20, 22-24, 27], and this is due to the additional complexities incorporated, when designing HVAC systems. Furthermore, although the use of local SA methods is well documented, the literature lacks in studies that utilise GSA methods, due to their complexity and computational costs. Rasouli et al. [22] have used local SA in modelling HVAC systems performance, and it has been also used by Sun [21], and Petersen and Svendsen [23] to evaluate the impact of building form, fabric, ventilation regimes, and climate on building energy performance. Examples of studies using FAST analysis to evaluate the impact of building form, fabric, climate,

along with some HVAC technologies parameters on energy consumption can be found in [28, 29]. There are also limited published applications of Sobol SA.

Based on the above, this objective of this research is to validate the potential of applying GSA methods in informing HVAC systems early design decisions. The study aspects which differentiate it from other analyses in the literature, are that it utilises Variance-based GSA, focusing on the variables affecting the energy technologies design, and sizing. In the next sections, the modelling framework developed is introduced, and the analysis results are discussed.

3. Methodology

3.1 Modelling Framework

A case-study is performed to explore the potential of GSA techniques, in informing energy technologies design decisions. The overview of the developed modelling framework is presented in Fig. 1, and the analysis workflow is as follows; first, the inputs samples are generated using MATLAB and R. Quasi-random Sobol sampling is used, owing to its better convergence [30]. The sample size is defined by the type of SA method. Next, energy modelling is performed in MATLAB, using the generated input samples. The model output in this case, is the energy consumption of the system. Then, the Factor Fixing analysis is carried out using Morris EE on the model results, to identify the least influential parameters. Based on the screening, the least important parameters are fixed to their mean/base value, and variance-based GSA follows. GSA is performed using the Sobol and FAST methods, to identify the top influential parameters (Factor Prioritisation). Finally, the results post-processing and interpretation follows.

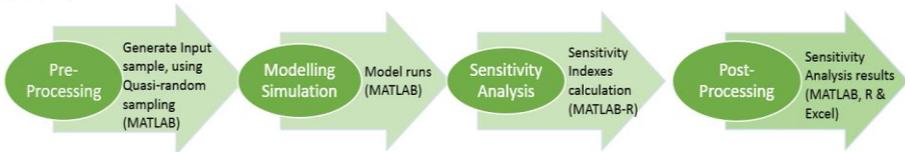


Fig. 1 The GSA workflow

3.2 Morris EE and Variance-Base GSA

Factor Fixing is first performed, using the Morris elementary effects method. The sensitivity indexes obtained by Morris are i) the μ/μ^* (or μ/μ^*), which is the average value of the elementary effects for each input parameter; and ii) the standard deviation (σ or σ), which provides an indication of the interactions between variables, or non-linearity. By plotting these two measures in a Morris chart, the parameters can be classified into those with high (high μ , high σ) and low influence (low μ , low σ) [30].

The FAST, and Sobol methods, as extended by Saltelli [15], have been deployed to perform *Factor Prioritisation*. The measures generated are the first-order sensitivity analysis index (S_i), and the total sensitivity index (S_{Ti}); S_i characterises the influence of

the X_i -parameter on the model output, whereas S_{Ti} estimates the influence of X_i -parameter along with X_i -parameter interactions with all other variables. The sensitivity indexes values are within the range of 0 to 1, and the higher the value of the index, the higher the influence to the model output is.

3.3 Model Description

Offices correspond to 25% of the EU non-domestic building floor-space [31], and are the second largest category in terms of floor-space after Retail (with 28%). In the UK, offices are responsible for 11% of the regulated final energy and carbon emissions of the non-domestic sector [32]. Therefore, for this case-study, a generic office cell has been selected, located in London (UK). Modules for the various components of the system were constructed, and connected to form the entire energy system (Fig. 2).

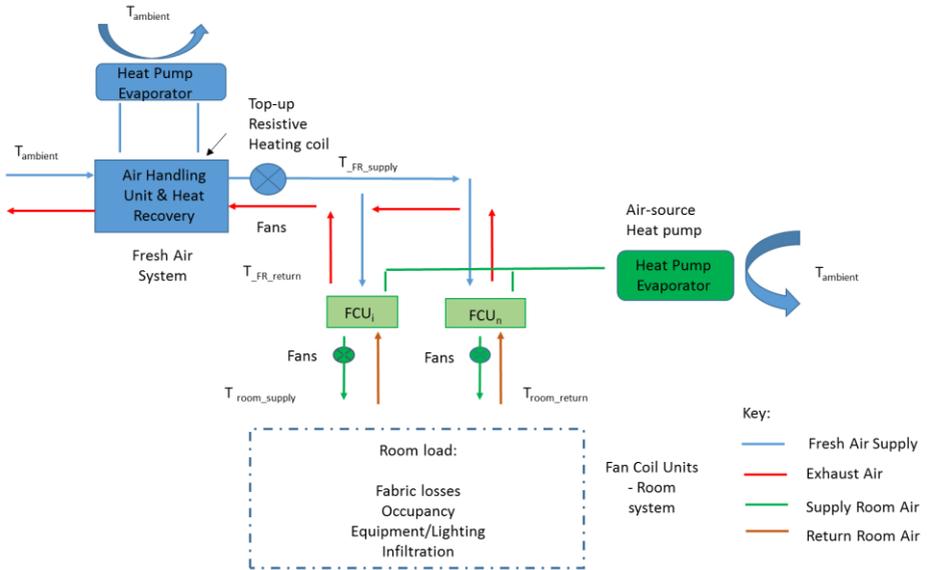


Fig. 2 Simplified system schematic

The main sub-systems are the followings:

Fresh air system with heat recovery: The system includes the air handling unit with the fresh air heat pump and top-up resistive heating. To evaluate the heat pump performance while ambient air conditions vary, the relationship between the COP/EER and temperature has been defined, based on data from heat pump laboratory tests, provided by Winkler [33].

Fan coil units (FCU) system: To cover the local room load a separate system is deployed; this of a Variable Refrigerant Flow (VRF) system with multiple indoor FCUs, and an outdoor heat pump.

AHU providing free cooling: For periods where cooling is required, modelling has been performed to see the impact of two alternative operating strategies to the energy consumption. The first operating strategy is the fan coil units to switch to cooling mode, and the second operating strategy involves the utilization of fresh air system free cooling potential, by ramping up the fans, prior to switching on the mechanical cooling system.

The energy technology model has been developed using MATLAB and GSA has been performed by coupling the technology model to alternative GSA packages in MATLAB and R [34-36].

3.4 Model Variables

As aforementioned, the context of this problem is the early design phases, where reliable estimates of the system load and energy consumption are required, but little is known. Therefore, the designers use typical values for the various loads (e.g. heat losses/gain on a per meter squared basis) to estimate the energy needs of the building. In this context, the design variables investigated using GSA are summarised in Table 1, along with their respective values, as these can be found in relative design guidance.

Table 1. Model parameters list, with their assigned probability distribution functions (pdf). Values selected in line with Refs. [3,7, 8, 37-41]

Parameter	Measure	Description	Assigned pdf
Ventilation Rate	ltr/s/person	Minimum fresh air requirements	~U (12, 15)
Area	m ²	Office space area	~U (1000, 8000)
Fresh Air Setpoint	°C	Fresh air supply temperature set-point	~U (16, 18)
Hpsize	%	Factor for sizing the fresh air heat pump	~U (0.6, 0.99)
COP	%	Factor to account for COP variation, from a base line	~U (70, 170)
Room DeltaT	°C	Room side air temperature delta T	~U (7, 10)
Troom_setpoint	°C	Room set point	~U (19, 21)
Fresh Air DeltaP	Pa	Pressure drop of the AHU fans	~U (100, 200)
FCURoom_DeltaP	Pa	Pressure drop of the FCU fans	~U (30, 50)
Eta_fan	%	Efficiency of fans	~U (75, 93)
Eta_motor	%	Efficiency of fans motors	~U (75, 92)
Eta_drive	%	Efficiency of fans drive	~U (75, 92)
Eta_HR	%	Heat recovery efficiency in the AHU	~U (0, 90)
Fans ramp up	%	AHU Fans ramping up to provide cooling, instead of FCUs	~U (0, 400)
Power density	W/m ²	Power requirements	~U(20, 25)
Occupancy	-	Occupancy	~U (0.1, 0.125)
Infiltration	ACH	Infiltration rate	~U (0.02, 0.5)
Lighting intensity	W/m ²	Lighting power requirements	~U (10, 15)
T_room_cooling	°C	Room set point (for cooling)	~U (23, 25)
Carbon intensity	kgCO ₂ /kWh	Carbon intensity of electricity	~U (0.46, 0.547)

4. Results and Discussion

The effect of each design parameter on the energy consumption (kWh/m^2) of a generic office cell in London is illustrated in Fig. 3. With reference to the numbers, the most influential variables are the heat pump efficiency, the heat recovery efficiency and the room temperature set-point. These parameters, along with the ventilation rate, the lighting/power density, the fresh air system pressure drop, and the room-side temperature differential are within the lines $\sigma/\mu^*=0.1$ and $\sigma/\mu^*=0.5$, which means that they have monotonic effect on the energy consumption. On the contrary, parameters related to the air circulation system (e.g. fans) have low linear effects.

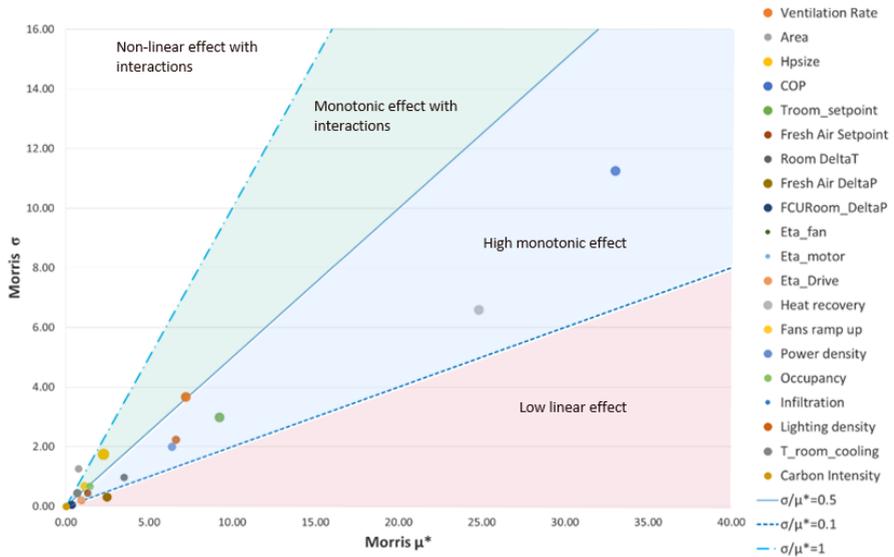


Fig. 3 Morris Chart

Variables such as the fresh-air temperature set point and the range of fans ramping up to provide the building with free-cooling have almost monotonic effects, but with interactions. A case in the point is the AHU fans ramp up level; an increase of the fans speed may increase the free cooling effect, and reduce the FCU load inside the room, but it also increases the fans energy consumption, since higher air flow rate is introduced into the control volume. Finally, the heat pump sizing factor (which accounts for the percentage of peak load covered by the top up heating coil) has non-linear effects and interactions. This is owing to the following; increase of the heat pump capacity results in low resistive heating energy consumption, however, the increase of heat pump capacity only to cover rare peak loads may result in reduced efficiency of the system at part-load operation over the year. Therefore, these results provide evidence that the screening method can identify the least/most influential variables.

Based on the Morris analysis results, a revised version of the model is considered which retains the uncertainty of only 12 medium/high important parameters. The FAST and Sobol methods are then applied and the results are presented in Fig. 4. In line with the numbers, the top influential parameters are the heat pump efficiency, the heat recovery efficiency and the room set-point. Additionally, in line with Fig. 5, these parameters are responsible for more than 80% of the energy consumption variability. The GSA results can therefore be utilised by the design team to prioritise the selection and sizing of the equipment that has the highest impact on the system performance, reducing the energy consumption and carbon emissions. They can also form the basis for further optimisation studies.

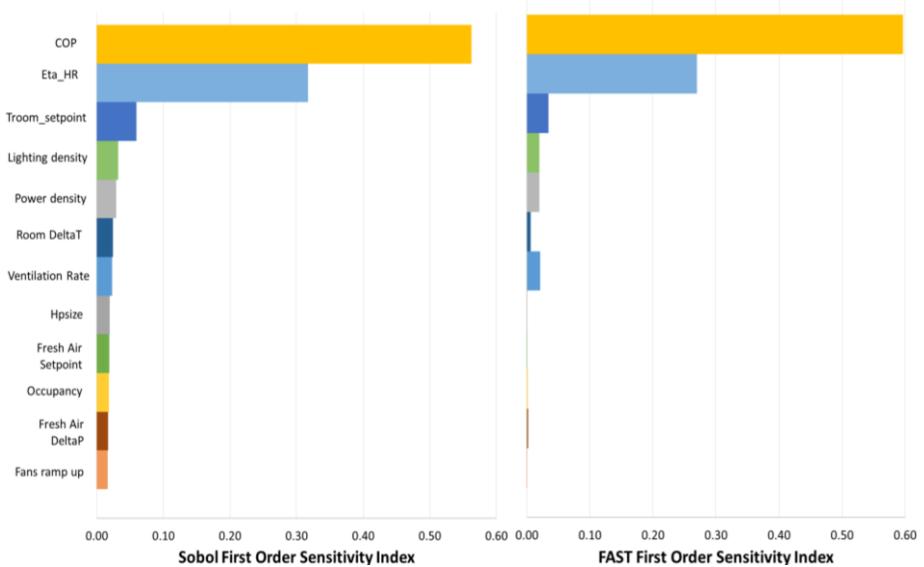


Fig. 4 FAST and Sobol analysis, first order sensitivity indexes

Finally, GSA can be used to inform the HVAC system sizing, providing credible load prediction at early design stages, accounting not only for the climatic conditions, but also for the impact of all system operational characteristics. This offers an alternative to the current sizing practices, which are based on fixed peak point estimates of the load, and may result in part-load and low efficiency operation over the year. To demonstrate better the use of GSA in HVAC sizing, the AHU heat pump load distribution is illustrated in Fig. 6. From this, the cumulative distribution for the system load can be also extracted (Fig. 6). Based on the results, a system capacity of approximately 29 kW (80% of peak estimate), can meet the peak heating load of every single hour with 95% probability. Therefore, this can be utilised by decision makers to evaluate if it is worthy economically, but also if there is, for example plant-room availability, or enough electrical infrastructure etc., to install the larger unit that covers the load under the most extreme conditions (37 kW), or select a lower capacity unit.

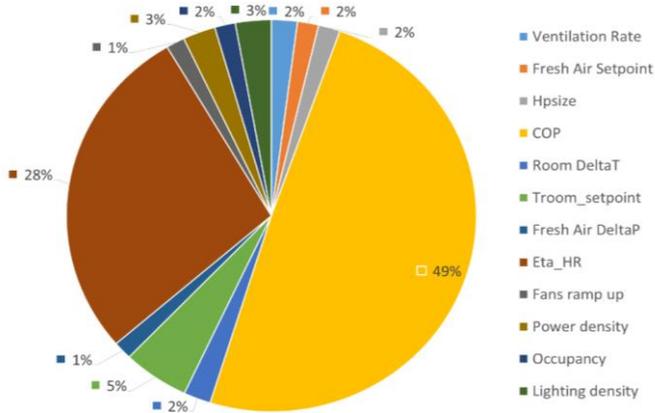


Fig. 5 Parameters contribution to energy consumption variability

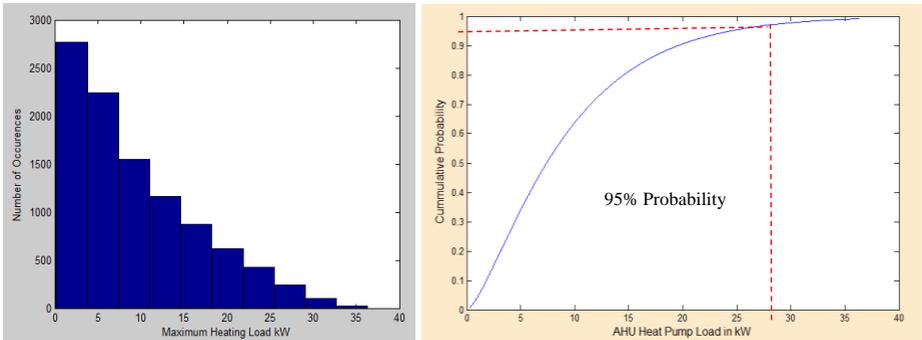


Fig. 6 Fresh air heat pump load (kW) probability distribution (left) and, cumulative distribution (right)

5. Conclusions and Recommendations

The design of efficient and low carbon HVAC systems requires thoughtful consideration of a wide range of variables, from the early design stages, where however, little is known regarding the system specification. In this paper, a GSA methodological framework has been proposed to deal with this uncertainty. The Morris EE analysis (*Factor Fixing setting*) results have indicated that variables including the fans efficiency, FCUs pressure drop, and the infiltration rate are the least influential, so therefore these can be kept fixed to any value within their respective range. Then the FAST and Sobol methods were used (*Factor Prioritisation setting*), to identify the most important design parameters. The results indicate that the heat pump and heat-recovery efficiency, together with the room temperature set point and the lighting power are responsible for almost 90% of the observed variability in the system energy consumption. Consequently, the findings can be used by the design team, at early

project stages, to focus first on the selection of only these important, and fewer design variables.

Moreover, the use of GSA to inform HVAC system sizing has been illustrated. The analysis provides the system load probability distribution curve, which can be utilised to define the performance levels that meet the stakeholders' intent. The GSA reveals that by sizing the heat pump system at 80% of the observed peak load estimate, the system will still be capable of covering the peak load of every single hour with a 95% probability.

To conclude the study has proven that GSA can be used to identify key influential variables of the buildings energy systems, in early project stages. The framework can be coupled to fully developed thermal models, in future phases. Finally, recommendations for further research include the use of GSA in the design of novel multi-generation technologies, to assess the influence of design parameters on their performance.

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