DYNAMIC SENSITIVITY ANALYSIS FOR PERFORMANCE-BASED BUILDING DESIGN AND OPERATION

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ABSTRACT

This paper presents dynamic sensitivity analysis as a novel design analysis tool for dealing with time-varying performance aspects in the built environment. We highlight some of the limitations of conventional sensitivity analyses in building design and present dynamic sensitivity analysis as an alternative solution. The first part of this paper introduces the basic principles of dynamic sensitivity analysis. In the second part, we illustrate its potential in a simulation-based case study of a typical office zone with external solar shading. The results stress the relevance of taking time-dependent factors into account in performance-based building design and operation. Dynamic sensitivity analysis can be a valuable tool to uncover such effects.

INTRODUCTION

Designing high-performance, low-energy buildings needs to become a mainstream activity to keep up with requirements prescribed in international environmental policies. The design option space for such buildings is large, and keeps on increasing with e.g., (i) the advent of innovative building envelope components, (ii) new integrated building and systems concepts, and (iii) more options for onsite renewable energy generation. These developments call for an integrated design approach and the application of performance-based strategies (Kolokotsa, Rovas, Kosmatopoulos, & Kalaitzakis, 2011). In this process, building performance simulation (BPS) has become the de facto standard as a design support tool for sustainable building design (Hensen & Lamberts, 2011). To adapt the design problem at hand to site-specific conditions and the clients' interests and requirements, it is important that the design team has the ability to navigate through the design option space in an effective way (Clevenger & Haymaker, 2011). Given the large number of alternative solutions, this task may not be straightforward.

Sensitivity analysis

Recently, a range of studies has identified the value of BPS-based sensitivity analysis (SA) as a powerful tool to support generation and assessment of design alternatives in the conceptual (Struck, 2012), as well as more detailed phases of the building design process (Hopfe, 2009; Tian, 2013). SA can be used for parameter screening; it helps in understanding relationships and the relative importance of design features, and allows the design team to focus their efforts on the subset of most influential parameters.

The mathematical basis for SA has been well-established (Saltelli et al., 2008), and because of ongoing developments in algorithms and user interfaces, SA is now able to bring much richer information to the design team, compared to the pioneering SA studies in the domain of buildings (e.g.(Lam & Hui, 1996; Lomas & Eppel, 1992)).

In typical applications, SA is used to generate parameter rankings based on the magnitude of sensitivity coefficients. The interpretation of the results is intuitive: parameters with highest sensitivity coefficients have the greatest influence on the selected performance indicator, and therefore deserve special attention throughout the design process. An additional feature of SA is that it can offer quick guidance in the search for (combinations of) design parameters that tend to lead to high performance buildings (Struck, De Wilde, Hopfe, & Hensen, 2009).

In building design applications, SA indices are usually calculated for scalar features like annual integrated energy demands (e.g. (Eisenhower, O'Neill, Fonoberov, & Mezić, 2012; Mechri, Capozzoli, & Corrado, 2010; Tian, 2013)) or peak loads (e.g. (Domínguez-Muñoz, Cejudo-López, & Carrillo-Andrés, 2010)). Building performance, however, is not a constant, and also the sensitivity in the mapping between input parameters and simulation output changes over time (Eisenhower & Mezić, 2012). The usual, consolidated, SA metrics are therefore insufficiently capable of providing insights into the evolution of sensitivity over time.

Dynamic performance aspects

Understanding the causes and effects of dynamic factors, however, is becoming more important, as it plays a prominent role in many of the unfolding performance-based trends in the built environment. The importance of transient effects is for example manifested in the following applications:

- *Performance indicators:* Dynamic utility tariff structures, requirements on the long-term balance in thermal energy storage systems, mismatch penalties between consumption and renewable production of energy;
- *Building and system integration:* minimizing peaks and duration of part-load operation, taking advantage of knowledge about variation in (seasonal) system COPs;
- *Building concepts:* Climate adaptive building shells, demand-side management applications.

Apart from these trends, time-dependent effects are also important in design cases with non-typical building operation. Examples include the strong intermittent operation in e.g., conference rooms, and the clear on- and off-peak periods in e.g., schools and buildings in the recreational sector. It is worthwhile to take advantage of this type of knowledge by adapting the building design and operation to the dynamic conditions.

Considering the relevance of these dynamic effects, we argue that it will become increasingly important to evaluate building performance not only on an annual basis, but to consider time-dependent effects such as the shape of load curves already in an early stage of the design process. Conventional SA techniques can support this type of analysis only to a limited extent (Perumal & Gunawan, 2011).

The objective of this paper is to describe dynamic SA as a method that is able to communicate how input-output sensitivity in BPS evolves over time. In the next Section, we introduce the principles of dynamic SA. After that, the use of dynamic SA is illustrated in a case where we analyze the impact of exterior solar shading.

DYNAMIC SENSITIVITY ANALYSIS

The concept of dynamic SA has been applied with success in various engineering disciplines, including the fields of modeling and simulation for nuclear reactor design (Auder, De Crecy, Iooss, & Marquès, 2012), agriculture (Lamboni, Makowski, Lehuger, Gabrielle, & Monod, 2009), biological processes (Sumner, 2012) and greenhouse design (Vanthoor, Van Henten, Stanghellini, & De Visser, 2011). In the buildings domain, (Lam & Hui, 1996) used conventional, local SA techniques to study the sensitivity of design attributes with respect to time-varying load profiles. They observed that sensitivity varies throughout the year, and hint at the potential of controlling individual parameters at different times of the year, but did not present a detailed analysis to test this assumption. To the best knowledge of the authors, the application of dynamic global SA in combination with detailed BPS models has not been investigated before.

The general methodology for SA of dynamic BPS output consists of six steps:

1. Select the performance indicators (PI) of interest, and identify the p design parameters and corresponding ranges as the subject of investigation.
2. Use an appropriate sampling strategy to create N input sets for the p design parameters.
3. Run N simulations in the selected BPS tool by varying the p input parameters. Within each simulation, the values for the perturbed parameters are kept constant. Save the simulation output $y(t)$ as time-series data.
4. Assemble all outputs in one matrix per performance indicator, such that:

$$\mathbb{Y} = \begin{pmatrix} y_1(1) & \cdots & y_1(t) & \cdots & y_1(T) \\ \vdots & & \vdots & & \vdots \\ y_i(1) & \cdots & y_i(t) & \cdots & y_i(T) \\ \vdots & & \vdots & & \vdots \\ y_N(1) & \cdots & y_N(t) & \cdots & y_N(T) \end{pmatrix}.$$

   Each row in $\mathbb{Y}$ represents the time-series output from $t = \{1,2,\dots,T\}$; each column contains the output at a given time for the N different input sets.
5. Perform SA for each individual column in $\mathbb{Y}$ by computing global sensitivity indices. For each PI and design parameter, this results in a sensitivity vector $\mathbb{S}$, such that:
   $\mathbb{S} = (s(1) \ \dots \ s(t) \ \dots \ s(T))$.
6. Plot the sensitivity indices versus time and analyze the results.

In principle, the use of dynamic SA does not presuppose a certain sensitivity index. Nevertheless, it is important to note from step 5 that a global SA is preferred for effective analysis in support of high-performance building design.

The outcome of dynamic SA is a vector rather than a scalar. As such, its contents are richer in information, but it also makes the representational challenge of dynamic SA outputs more complex (Helton, Johnson, Sallaberry, & Storlie, 2006). The common use of if-then-else logic and discrete operation schedules in BPS models adds further complexity to the post-processing phase. An example of this is the on/off switching of heating and cooling equipment, which tends to lead to sudden changes in energy demand. Such effects may cause interpretation problems in the analysis phase, because they lead to a non-smooth evolution of sensitivity. To smooth out such short-term fluctuations, it is useful to analyze the results after calculating a moving average of the raw output (Vanthoor et al., 2011). This method is preferred above the use of discrete (e.g., daily or monthly) averaging or integration intervals because it better preserves the building dynamics. An additional benefit of using moving averages is the fact that it can highlight longer-term trends in the data. Doing so offers additional pieces of design information that would otherwise go unnoticed.

The case study presented in the next Section will demonstrate dynamic SA and the purpose of the smoothing technique in more detail.

DEMONSTRATION EXAMPLE

Exterior shading systems, like overhangs and shading fins, are effective design features for managing the role of solar heat gains in a building's energy balance (Lee, Selkowitz, Bazjanac, Inkarojrit, & Kohler, 2002). The effects of fixed solar shading, however, are not positive all year long, because it also reduces the use of passive solar contributions in colder periods (Hastings, 1995). The application of permanent exterior shading moreover limits the exposure to positive non-energy related aspects of daylight utilization. Larger shading elements are not by definition better, and careful dimensioning is therefore an essential step in the process of achieving high-performance building design.

Case study details

The method for dynamic SA will be illustrated in a case study where we analyze the impact of exterior solar shading design on the energy performance of a typical office zone. The room is located on an intermediate floor, and is surrounded by similar spaces and a corridor at the back. The external façade of the zone faces southeast. Energy demand for heating and cooling is assessed in this study by using the TMY2 weather data for Boulder, CO, USA. Details of the case study building are presented in Table 1.

Table 1: Case study details

Occupancy	1 person: 8 – 17 h
Internal heat gains	Lighting: 10 W/m^2 Equipment: 15 W/m^2
Orientation	Southeast (45˚)
Location	Boulder, CO, USA.
Dimensions (LxWxH)	4.5x3x2.9 m
Heating set point	Day: 20 ˚C, Night: 15 ˚C
Cooling set point	Day: 25 ˚C

Figure 1 shows an isometric view of the solar shading geometry. The shading system consists of two vertical shading fins (A and C) and a horizontal overhang (B). The length of each shading element (perpendicular to the façade) is varied independently between 0 and 1 meter, with uniform probability.

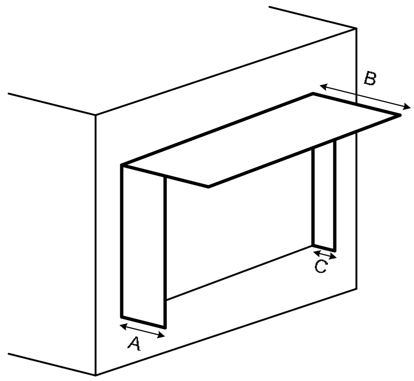

Figure 1: Façade geometry of the building model

Simulation strategy

The Latin Hypercube sampling method was selected to generate descriptions for thirty different shading configurations, because it ensures good coverage of input space (Tian, 2013). A UNIX script was written to perform annual ESP-r simulations for each case in the sample. In ESP-r, the effect of exterior shading was modeled by defining obstructions in the **.geo* files and activating the *ish* shading module (Clarke, 2001). At each simulation time step, the instantaneous heating and cooling energy demand was recorded. Post-processing of the simulation output was carried out with the help of the 'Statistics Toolbox' in Matlab. The standardized regression coefficient (SRC) (Tian, 2013) was selected as sensitivity index in this study.

Results

Figure 2 shows the output frequency distribution for the thirty different design variants. The large spread in results suggests that the design of exterior shading has a significant impact on building energy demand, and that a well-informed design process is required to achieve good energy performance.

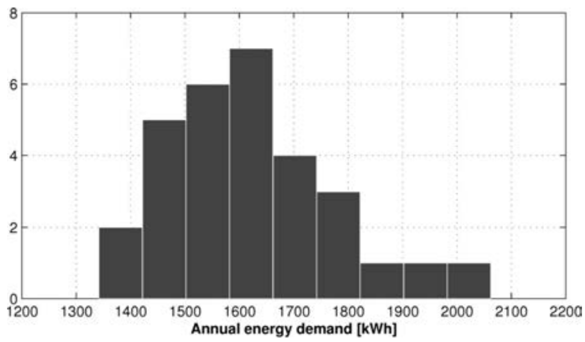

Figure 2: Frequency distribution of the sum of annual heating and cooling energy demand

A "conventional" SA was carried out to evaluate the individual impact of each of the three shading elements on energy performance. The standardized regression coefficients were calculated and are presented as a tornado plot in Figure 3. The Figure shows that the length of the horizontal overhang (B) has a very significant impact on energy performance.

The sensitivity indices for the vertical fins are almost equal and much lower than for the overhang.

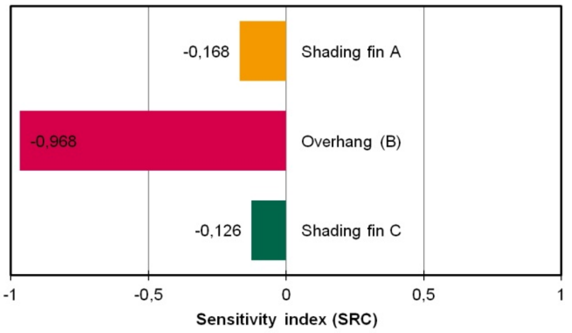

Figure 3: Result of conventional SA

The sign of the sensitivity index for all three design parameters in Figure 3 is negative. This finding implies a negative correlation between shading length and energy demand, and therefore indicates that increasing the shading length will lead to a decrease in annual energy demand, and vice versa.

To gain more insights into the temporal aspects of sensitivity, we performed a dynamic SA by following the methodology presented in the previous Section. The graphs in Figure 4 show the evolution of sensitivity over the year for each of the three shading elements (A-C).

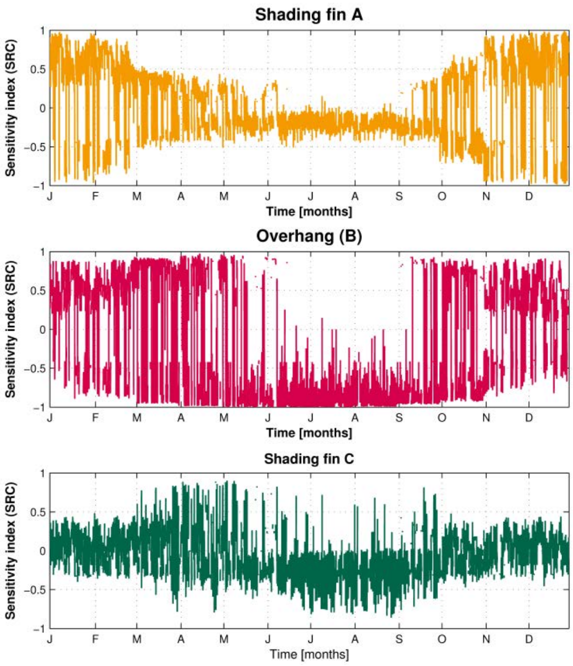

Figure 4: Results of dynamic SA for shading fin A, overhang (B) and shading fin C.

From the graphs in Figure 4, it becomes immediately clear that the sensitivity indices are not constant, but a function of time. Some longer-term, seasonal effects can be observed, but the graphs are mainly dominated by the high degree of short-term fluctuations. On the one hand, insight into these high-frequency fluctuations is desired as it contains useful information about the variations that occur from time step to time step. On the other hand, however, these diurnal fluctuations contain irrelevant side-effects that arise from discontinuities in the model set-up, and the fact that it is not possible to calculate sensitivity indices at time steps with zero energy consumption. Distinguishing between these effects and interpreting the results by visual inspection of the raw output data only, is difficult. As a consequence, the results in Figure 4 have only limited value in extracting useful design information for decision support in the design process.

To aid in the further analyses, we calculated the 24-hour moving average of the sensitivity indices. Doing this introduces a smoothing effect that allows us to (i) disregard (sub-)hourly variations, and (ii) shift the focus of attention to day-to-day changes. The results are presented in Figure 5.

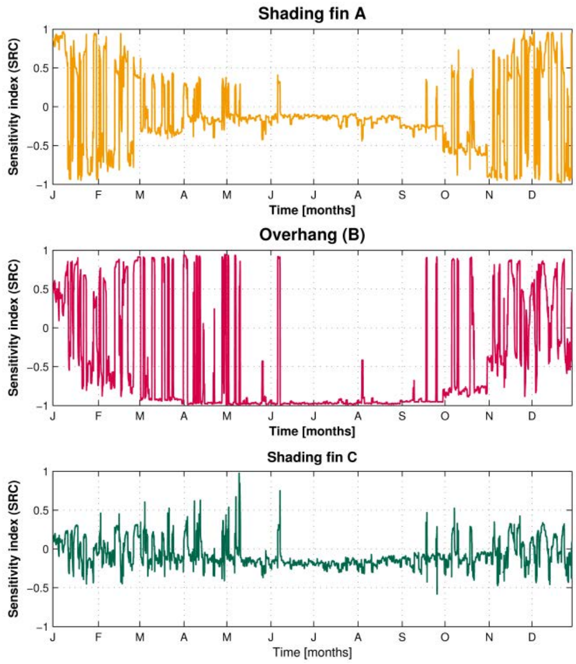

Figure 5: Results of dynamic SA – 24-hour moving average.

The results in Figure 5 partly correspond with what was found in Figure 3, but also show some notable differences. During most parts of the year, the absolute value of the sensitivity index for shading fin C is significantly lower than the values for shading fin A. This effect can be explained by the building orientation: the external façade faces southeast. As a consequence, shading fin C is only effective in preventing the morning sun from entering the building. The effect of shading fin A on the other hand can be noticed during more of the occupied hours. This period happens later during the day, when not only the average intensity of solar radiation, but also the influence of solar gains on energy demand, is relatively high.

Compared to Figure 4, the results in Figure 5 feature milder fluctuations and no longer include discontinuous jumps. The variations in Figure 5 resemble the type of natural variability in sky conditions that is also present when one calculates a 24-hour moving average of direct solar radiation. In winter, spring and autumn, the usefulness of solar shading is determined by the complex interplay between ambient boundary conditions and the building's momentary energy balance. During a series of cloudy days, for example, it is desired to allow solar radiation into the building as much as possible. In Figure 5, such an interval is characterized by a relatively long period of positive sensitivity indices. The opposite effect, in sunny conditions also becomes evident from Figure 5.

For improving building performance, the results in Figure 5 suggest that it would be worthwhile to consider the use of movable shading devices or awnings rather than permanent systems studied here.

Even more information on longer-term trends can be obtained by ignoring day-to-day variations. This was achieved by calculating the ten-day moving average of the sensitivity indices. The results are shown in Figure 6

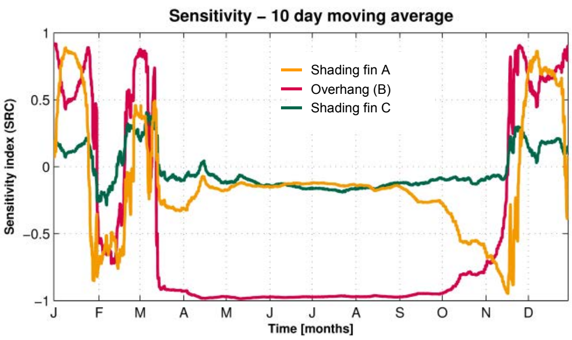

Figure 6: Results of dynamic SA – ten-day moving average.

In 'summer' months, approximately from April to the end of September, the horizontal overhang appears to be the only sensitive variable. In this period, cooling needs are high and dominant in the building's energy balance. At the given latitude (40˚N), the solar altitude angle in summer is high and as a result, the amount of solar radiation that is intercepted by the vertical shading fins is relatively low. A horizontal overhang on the other hand is very effective in reducing energy demand, as Figure 6 shows.

Around the end of January and the end of November, a sudden change in the sensitivity indices for shading fin A and overhang B is observed. Especially the sign change is an interesting finding, because it clearly signals the potential for seasonal shading modes (Lorenz, 1998). In summer, energy performance benefits from large shading elements; in winter it is preferable to have no shading obstructions. Considering these longer-term dynamic effects, it seems worthwhile to investigate the possibility of designing solar shading as an adaptable add-on façade element. This finding fits well in the philosophy of long-term climate adaptive building shells (Loonen et al, 2011; 2013), and offers opportunities for innovative design solutions (Bitrou, 2006; Kassab & Love, 2005)

Perhaps even more important than the previous finding is the fact that dynamic SA can also be useful to support the operational decision for the best transition moment between winter and summer mode. The subtlety of this problem is illustrated by the relatively cold and cloudy period in March which causes a steep shift of sensitivity indices in the opposite direction. These effects may be missed by conventional shading design tools, which usually only consider boundary conditions as input, instead of the feedback about the actual interaction between climate and building load characteristics.

DISCUSSION

Solar shading design

This paper illustrated the basics of dynamic SA by means of a relatively simple example: only three design parameters were varied, and the effects of solar shading are only noticeable during daytime. The results show that the application of dynamic SA offers additional benefits, compared to conventional SA. Using conventional SA, Figure 3, for example, indicates overhang length (B) as the only sensitive parameter. Dynamic SA verifies that the design of shading fin C is indeed relatively insignificant for energy performance. For shading fin A, however, this is not invariably true. The significant negative effect of shading in winter is counterbalanced by the positive effects in summer. Such effects are easily noticed in the output of dynamic SA, but are masked in annually-integrated sensitivity metrics.

Compared to basic (Etzion, 1992) as well as more advanced (Sargent, Niemasz, & Reinhart, 2011) solar shading design analysis tools, the application of dynamic SA also offers advantages. Dynamic SA is able to effectively visualize the interrelated time-varying effects between control of the amount of solar gains and the building's thermal response. The conventional tools tend to be based on solar conditions only, and cannot provide this type of information.

Application area for dynamic SA

The scope and level of detail of the demonstration example is relatively limited compared to the type of design challenges that is usually faced in high-performance building design. The case was devised to illustrate the potential of SA, and also because it allowed for relatively straightforward representation of the results. In principle, we see no reasons why the method cannot be applied to design studies with more complexity. However, when the number of design variables and interactions increases, it may become challenging to rank different design parameters, especially when their effects are conflicting. In addition, it still needs to be tested how the method behaves in the presence of e.g. multiple performance indicators, or detailed HVAC system simulation.

The added value of dynamic instead of conventional SA is most pronounced in "non-typical" cases. The biggest contributions are expected in designs where building or system components can be actuated in response to dynamic conditions throughout the operational phase (e.g. adaptable façades or advanced systems control).

As a potential drawback of the method presented in this work, the effects of high thermal inertia should be mentioned. It is well-known that thermal mass causes both attenuation and time-shifts in the building's energy balance. When the influence of thermal mass becomes large (e.g. in thermally activated building systems), the instantaneous effects are typically spread over multiple time-steps. This may cause too much interference in the analysis of the different energy flow paths and may prevent dynamic SA from being useful in such applications.

Possible extensions

The analyses in this study employed the standardized regression coefficient as the metric for assessing the level of sensitivity. This SA index is particularly useful here. Apart from information about the relative importance of each parameter, the sign of the coefficient also provides valuable guidance to the design team as it points to the most favorable subset of the design option space. A limitation of this approach is that the results are only reliable when the model response is monotonic and approximately linear. In more complex settings with wide parameter ranges, these conditions may not apply. Recent studies have shown that variance-based uncertainty and sensitivity techniques (e.g. ANOVA or Sobol methods) can provide superior results compared to other methods (Saltelli et al., 2008; Tian, 2013). Especially the use of nonparametric regression techniques seems promising for strategic exploration of the design option space in high performance building design (De Wilde & Tian, 2010; Storlie, Swiler, Helton, & Sallaberry, 2009). Future research should investigate how these methods can be deployed in the frame of dynamic SA.

Although the application of dynamic SA in the building domain is relatively new, it can build upon solid research work from other engineering fields. One promising line of research aims at further exploiting of (periodic) patterns in the dynamics of time-series output (Auder et al., 2012; Campbell, McKay, & Williams, 2006; Lamboni, Monod, & Makowski, 2011; Sumner, 2012). Statistical techniques like principal component analysis (PCA) can be used to identify a reduced set of composite variables which explains the majority of variation in the output. Such an approach is mainly attractive because it can greatly reduce dimensionality of the output, and thereby produce results that are easier to interpret without loss of information. Transferring these principles to the domain of building design, and finding solutions that circumvent the problems related to the discontinuities underlying most BPS models, is not yet done, and therefore a valuable direction for future research.

CONCLUSIONS

While traditional parametric SA provides a powerful tool for studying input-output relationships in building design, its suitability in inferring the dynamic aspects of building performance has not been properly addressed. In this study, we present a method for dynamic SA of BPS output that is able to communicate how sensitivity evolves over time. Results from a case study demonstrate how dynamic SA in combination with a smoothing technique can be used to identify which design parameters are influential at particular times of the year. This can deliver a new type of performance information to the design process, and also provides useful cues regarding which operational actions can improve building performance. This study concludes that dynamic SA has the potential to become a valuable addition in the range of decision support tools to cope with the growing design option space in the search for high-performance buildings. A logical next step would be to test the potential of dynamic SA in a case with more real-world complexity.

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