The Efforts Towards Development of an Energy Optimization Dynamic Simulation Tool

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Abstract

Building retrofit at large scale needs to optimize opposing objectives, such as energy, cost, and comfort, and consider various constraints simultaneously. This complex task requires reliable tools that evaluate different retrofit scenarios for buildings and promptly inform the decision making. The current tools commonly lack automatic, multi-objective, and thorough retrofit scenario evaluation. This contribution presents the efforts towards the development of an automated building retrofit decision-making tool that can gauge cost-effective retrofit options using the EnergyPlus dynamic energy simulation software and the multi-objective optimization genetic algorithm of DAKOTA. This tool identifies the optimal alternatives for building elements and systems through an automated process, to maximize building energy performance and minimize the investment cost. This paper describes the technical procedure of development of the retrofit optimization tool. It then focuses on reducing its execution time to enable real-time simulation-based evaluation through adjusted parameter setting of the simulation engine and optimization algorithm, and finetuning the connection points.

Introduction

With the ever-increasing population of urban areas, the building sector can play a significant role in reducing energy demand and associated carbon emission by large scale energy retrofit actions (Pachauri *et al.*, 2014). The current energy performance projection tools lack automatic, real-time, multi-objective retrofit scenario evaluation for developing optimized strategies for energy, carbon, and cost-saving, besides enhanced comfort, and wellbeing. In practice, new building design or renovation problems usually deal with conflicting objectives such as minimizing energy consumption versus minimizing construction cost. Hence, there is a growing interest for the use of multi-objective optimization algorithms in the building industry (Heurix *et al.*, 2013; Nguyen, Reiter and Rigo, 2014; Dalla Mora *et al.*, 2018; Sharif and Hammad, 2019). Urban-scale building energy model (UBEM) programs either use simplified building energy models such as CitySim (EPFL, 2020) or employ physics-based dynamic energy simulators such as URBANOpt (NREL, 2020) and CityBES (LBNL, 2020) that use EnergyPlus.

EnergyPlus is an advanced tool for more accurate UBEM evaluations because it enables modelling urban microclimate conditions for assessing urban heat island effect and long-wave radiant exchange for evaluating urban canyon effect (Tianzhen, Langevin and Sun, 2018). Depending on the complexity of the building model, the EnergyPlus simulation run can be computationally expensive and take minutes or hours for full analysis. In 2009, LBNL released a report declaring that the EnergyPlus run time depends on these major factors: building model energy features; user-specified simulation parameters setting; source code version and compiler; computer platform hardware and operating system (Hong, Buhl and Haves, 2009; Shi and O'Brien, 2018). In the first few versions of EnergyPlus, run time was reduced considerably. The run time reduction, however, has slowed down due to the lack of simulation engine performance optimization on multi-thread central processing unit (CPU) and complex algorithms added to the simulation engines (Hong, Buhl and Haves, 2009; Shi and O'Brien, 2018).

To evaluate and find the optimum solutions for multiple conflicting objectives with the least number of attempts, EnergyPlus should be paired with an optimization algorithm, such as the evolutionary algorithms (EA). EAs are based on survival of the fittest and coupling them with EnergyPlus requires a considerable number of function evaluations of the design surface to find the Pareto front solutions (Maarouf *et al.*, 2015). For this approach to prevail and enable real-time retrofit scenario evaluation at the urban level in the professional practice, the optimization time must be reduced considerably.

Machine Learning (ML) emulators (also known as response surface models, metamodels, or surrogate models) are most widely used when the simulation costs are high. ML approximates the optimization problem function by mimicking the behaviour of the simulation model as closely as possible while being computationally cheaper to evaluate (Prada, Gasparella and Baggio, 2018). However, ML emulators can only consider a limited number of design variables to do a quality estimation (Hopfe *et al.*, 2012). Moreover, most studies of metamodel techniques in building performance simulations either consider limited building use type, geometry, limited retrofit, or design improvement scenarios (Østergård, Jensen and Maagaard, 2018). Given that robustness and reliability of ML emulators for optimization of all building types in real practice is undecided (Prada, Gasparella and Baggio, 2018), a dynamic simulation engine is more desirable to achieve more accurate energy use projection on a complex design surface such as a large number of energy retrofit options.

In building optimization studies, objective function derivatives (gradients) are often unavailable analytically. Therefore, Derivative-Free (DF) algorithms, which can deal with both linear and nonlinear problems with discontinuities are suitable for optimization in buildings and broadly used (Bamdad Masouleh, 2018). To avoid local optima and find the global Pareto optimal retrofit solution in non-convex, discontinuous, and multi-modal solution spaces, Population-based Global search (meta-heuristic) algorithms, such as Genetic Algorithm (GA), Ant Colony, or Particle Swarm are used (Nguyen, Reiter and Rigo, 2014; Bamdad Masouleh, 2018; Kheiri, 2018). GAs are more widely used in building design optimization compared to other techniques (Asadi and Geem, 2015). One reason is more prevalent availability of GAs in optimization engines and more optimization control and tuning parameters, including fitness assignment procedure, elitism, diversification, or constraint handling approaches.

A selected number of optimization engines commonly used in building and CAD optimization literature were reviewed and compared in Table 1 to choose a well-performing optimizer that allows the use of a simulation engine directly. Table 1 is an updated version of the table developed by Nguyen *et al.* (Nguyen, Reiter and Rigo, 2014). The optimization engines must be capable of handling constraint functions and offer the possibility of extending the optimization algorithms. Moreover, to reduce the simulation run time, the optimization process should allow for parallel and cluster computing, as well as cloud-based calculation. DAKOTA (Sandia, 2020) is an object-oriented, extensible, open-sourced engine that has these capabilities and can be used for optimization, design exploration, uncertainty quantification, sensitivity analysis and more. It includes advanced optimization strategies and enables parallel simulation. MOBO is another open-sourced, generic optimization engine that is used for building optimization; however, the development of MOBO was discontinued in 2014.

EAs available in DAKOTA for derivative-free global optimization of categorical or discrete variables are coliny-ea and, called multi-objective genetic algorithm (MOGA). MOGA maintains the non-dominated solutions in the population through two operators. The “domination count” fitness assessor ranks the population members based on the number of other members that they dominate and “below limit” selection operator chooses the members with fitness above a set limit (Adams *et al.*, 2019).

Given the growing interest and recognition of the value of the integration of optimization into the buildings design or retrofit, several studies provide comprehensive reviews on optimization application in the building industry in recent years (Attia *et al.*, 2013; Machairas, Tsangrassoulis and Axarli, 2014; Asadi and Geem, 2015; Mavromatidis, 2015; Waibel *et al.*, 2019; Costa-Carrapiço, Raslan and González, 2020). The gaps identified are:

1) Knowledge of optimization tools suitability and algorithm parameter settings for different purposes, in particular, reliable for various building types, objectives, and constraints;
2) Technical details of optimization tools integration with simulation engines and scenario evaluation in white- or black- box models that can automatically incorporate both qualitative and quantitative objectives; and
3) Knowledge of approaches for improving the execution time to enable real-time scenario evaluation.

Table 1: Comparison of optimization engines that enable multi-objective optimization

Optimization Engine	Parallel computing	Multiple algorithms	Handles constraint functions	Algorithmic extensibility	Surrogate model	Open-source	Cloud & Cluster computing	Cost function flexibility	Discrete & continuous	User interface	Generic or (building specific)
DAKOTA (Sandia, 2020)	+	+	+	+	+	+	+	+	+	+	+
MOBO (Aalto University, 2013)	+	+	+	+	–	+	–	+	+	+	+
modeFRONTIER (ESTECO, 2020)	+	+	+	+	+	–	+	+	+	+	+
HEEDS (Siemens, 2020)	+	+	+	+	+	–	+	+	+	+	+
Optimus (Noesis Solutions, 2020)	+	+	+	+	+	–	+	+	+	+	+
MATLAB (MathWorks, 2020)	+	+	+	+	+	–	+	+	+	–	+
ModelCenter (Phoenix Integration, 2020)	–	+	+	+	–	–	–	+	+	+	+
BOSS quattro (NAFEMS, 2020)	+	+	+	+	+	+	–	+	+	+	+
GenOpt (LBNL, 2016)	+	+	–	+	–	+	–	+	+	–	+
BEopt™ (NREL, 2018)	+	–	–	+	–	+	–	–	+	+	–
jEPlus+EA (Zhang and Korolija, 2019)	+	+	–	–	–	+	–	–	+	+	–
“+” means Yes; “–” means No.											

This study explores these knowledge gaps to identify the right tools and techniques required to develop a reliable, automatic building retrofit optimization tool that can promptly pinpoint solutions to maximize the building energy performance and minimize the investment cost. The focus is on whole building retrofits optimization; therefore, system-level cost analysis, inter-zonal heat transfer, lighting/heating fuel relationships are not part of the scope of this study. The next section describes the process followed in choosing an optimization engine and algorithm and designing the retrofit optimization tool. The results discuss the performance of the developed tool and the results of the enhancement procedure to reduce the execution time. The paper concludes with highlighting the key findings and the plan of work to integrate the tool with real building data for more comprehensive assessment at the urban scale.

Methodology

The retrofit optimization flow follows the steps shown in Fig. 1 and described below. Following a comprehensive review of the most widely used engines for multi-objective optimization in the building industry (Table 1), DAKOTA (version 6.10) was chosen to be linked to EnergyPlus (version 8.0). MOGA Pareto-ranking was used to rank the population and assign a fitness value according to the least cost and annual energy use, then choose the members with fitness above a user-specified limit.

This study uses the primary building data, including location, use type, geometry, HVAC systems, and occupancy of the U.S. Department of Energy (DOE) Commercial Reference Building Models of the National Building Stock. These EnergyPlus models comply with the minimum requirements of the corresponding ANSI/ASHRAE/IESNA Standard, and include 16 commercial building types in 16 locations, with 3 vintages (new, post-1980, and pre-1980 construction) (Deru *et al.*, 2011). The case studies in this paper are chosen from the DOE reference building models (step 1, Figure 1). In the real application where primary building data is available, the reference models will be modified based on the characteristics of the relevant single building or representative building stock for large scale retrofit evaluation.

In this paper, four building types of the DOE commercial reference building models with various energy feature complexities were examined: middle-sized office, primary school, secondary school, and hospital. The details of these building models are described in Table 2.

Next, using default calculation parameters and relevant weather data, EnergyPlus is ran to calculate the annual energy consumption as the baseline building energy use (step 2, Figure 1).

Table 2: Four DOE commercial reference building types with different energy feature complexities were considered

Building	Footprint Shape	Floors	Floor Area	HVAC
Middle-Sized Office	Rectangular	3	4,980 [m^2]	1 central VAV with water-cooled chillers and hot-water boilers. Perimeter zones have reheat-boxes
Primary School	E shape	1	6,871 [m^2]	4 packaged VAV with hot-water boiler and 1 Packaged Single Zone (PSZ) with gas furnace
Secondary School	E shape	2	19,593 [m^2]	3 PSZ with gas furnace and 4 central VAV water-cooled chillers and hot-water boilers
Hospital	Rectangular	5 +basement	22,428 [m^2]	2 central VAV with water cooled chillers and hot water boilers

The costed retrofit option library was developed, including a combination of building envelope construction, HVAC equipment, lighting, and control systems. In this study, six types of energy conservation measures (ECM) are considered, namely, adding insulation to roof and walls above-grade and replacing the fenestration, lighting, and heating systems. The energy-related performance parameters, level of disruption, and unit cost of each ECM are included in the retrofit options library.

To perform a constrained optimisation, infeasible domain is usually formulated as boundaries of the objective functions, such as thermal comfort, budget, or payback. Many studies consider a database of retrofits without filtering the recommendations based on existing building physics limitations and user-specific requirements (Costa-Carrapiço, Raslan and González, 2020). In real practice, in addition to bounded objective function, having an accurate database filtering is crucial to ensure: the minimum regulatory requirements are met; the appropriate upgrade or alternative are chosen for building elements and surface types; and building elements are upgraded for better, and only if required. Here, in step 3, the database is filtered considering:

1. The latest ASHRAE 90.1 (in this case 2016) minimum compliance requirements for each building element and existing building properties, whichever is more energy efficient. These include thermal transmittance of the roof, walls above-grade, fenestration; solar heat gain coefficient (SHGC) of fenestration; and lighting power density.
2. Building physics limitation, for example, if there is an air gap in the wall, cavity insulations such as loose fiberglass or mineral wool are considered, and otherwise internal and external insulation options can be applied
3. User-specified restrictions. For the wall example, it could be that the user does not want to change the building façade and hence external insulation options should be excluded.

Next, DAKOTA optimizer receives the retrofit scenarios by either alternatives or upgrades for building elements and systems, through a query of the viable retrofit options (step 4, Figure 1). The EnergyPlus model of each alternative scenario is automatically created (step 5) by modifying the initial building using the Python Eppy scripting language (PyPI, 2019) and ran to calculate the annual energy use (step 6). The retrofit scenario's cost is separately calculated using the unit cost of the retrofit and applicable surface area or the number of components (step 7). EnergyPlus and cost calculation are run concurrently based on the set number of parallel simulations until there are no more new retrofitted building designs in one population. Then, the results of these functions for all the population members are fed back to DAKOTA, and DAKOTA creates the next population members. Steps 5 to 7 in Figure 1 will be repeated until convergence criteria are met. Consequently, the multi-objective optimization identifies retrofit scenarios that minimize the building energy consumption for the minimum investment cost and presents the list of Pareto optimal retrofit solutions to the user (step 8, Figure 1).

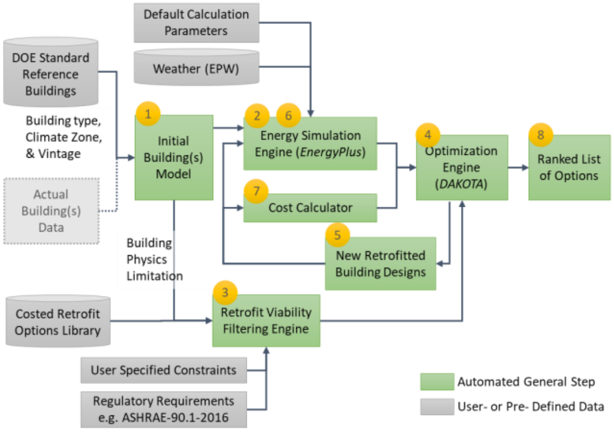

Figure 1: Automated process to maximize the building energy performance and minimize the investment cost

To reduce the total run time of the retrofit optimization tool, several solutions were explored. In the first place, following the example of Hong et al. (Hong, Buhl and Haves, 2009), the influence of EnergyPlus simulation settings on execution time was studied independently to identify the parameters with major influence. The influential parameters were then combined to study their overall impact on run time and annual energy use projection. Table 3 presents the EnergyPlus setting parameters that have significant impact on simulation time.

The efficiency of retrofit optimization tool was explored in three stages. First, the effect of the number of parallel simulations was studied on a server with 4 Cores, 4 Logical Processors, and 12GB RAM. Parallel simulation can significantly reduce the run time by dividing the simulation runs to multiple processor cores (Hong, Buhl and Haves, 2009). DAKOTA can run several simulations concurrently, up to the population size. The “evaluation tiling” method was used, which partitions a single processor to run multiple application jobs, each requiring several processors (Adams *et al.*, 2019). This method is suitable as the EnergyPlus engine requires modest memory count.

Secondly, the connection processes of the EnergyPlus and DAKOTA coupling in the optimization algorithm was reviewed and finetuned through logging the duration of each iteration and timestamp of main scripts, including:

- DAKOTA MOGA process of creating population members from the viable retrofit scenarios (step 3 and 4, Figure 1),
- Application of new retrofit scenarios to the building model (step 5),
- EnergyPlus (concurrent) simulations (step 6),
- Cost calculations (step 7),
- Exporting EnergyPlus and cost calculation results of all the members of the population to DAKOTA (back to step 4).

Finally, the MOGA optimizer fitness assessor and selection operator parameters were reviewed.

The key performance indicators (KPI) considered for assessing run time improvement were efficiency and robustness. Efficiency is the run time saving percentage, which was calculated as the average run time for all the evaluations. The solution was considered robust when the performance was similar under all sorts of different problem settings and starting conditions.

Efficiency was redefined, and the quality of the solution was considered as additional KPI when studying the MOGA parameter settings to test the algorithm’s fitness. Efficiency was defined as the number of evaluations to reach the Pareto front. Quality of the solution was the measure comparing the predicted Pareto front and the true Pareto solution.

Discussion and result analysis

The retrofit optimization engine was executed in various design settings for four building types (middle-sized office, primary school, secondary school, and hospital) and considering 11088 different combinations of possible retrofit scenarios, including glazing, lighting, and boiler replacement, as well as adding a roof and wall insulation.

Appraisal of run time under different EnergyPlus simulation settings revealed several parameters with significant impact on execution speed, which are listed in Table 3. The “reduced run time setting” for these influential parameters were then compared against the default DOE reference building setting to report their total impact on run time and annual energy use projection (Figure 2). The length of the run period is a deciding factor, yet it is crucial to optimize building performance over the whole year, considering all seasons. Since for comparison, only monthly and annual energy consumption results were needed, hourly time step was found sufficient. The “simple” and “simplecombined” surface convection algorithms lead to the least execution time. In these methods, the heat transfer coefficient is assumed constant for inside and reliant on surface roughness and wind speed for outside surfaces.

Since the buildings do not have detailed exterior shadings or complex geometries, minimal shadowing method is appropriate to calculate solar distribution and reflection.

Reducing the number of warmup days not only does not improve the run time but also may result in severe errors as the warmup may not converge. In this study, 25 warmup days were considered.

Figure 2 shows that the proposed EnergyPlus parameters setting can reduce the run time by at least about a third while overestimating the annual energy use by less than 10%. Hence, the proposed setting was used for subsequent assessments.

Table 3: EnergyPlus parameters settings

Simulation Input	EnergyPlus IDD Object	Impact on Run Time	DOE Reference Building Setting	Reduced Run Time Setting
Length of Run Period	RunPeriod	Major	Whole Year	
Number of loads calculation time steps in an hour	Timestep	Major	4 (15 minutes)	1 (60 minutes)
Heat balance solution algorithm	HeatBalanceAlgorithm	Major	CTF	
Calculation algorithm for convection heat transfer of inside and outside surfaces	SurfaceConvectionAlgorithm:inside	Major	TARP	Simple
	SurfaceConvectionAlgorithm:outside	Major	TARP	SimpleCombined
Solar distribution and reflection calculation algorithm (solar shading)	Building	Major	FullInteriorAndExterior	MinimalShadowing
Minimum HVAC time step and maximum HVAC iterations	ConvergenceLimits	Minor	20 Maximum HVAC Iterations	
		Major	2 Minimum Plant Iterations	
		Minor	8 Maximum Plant Iterations	

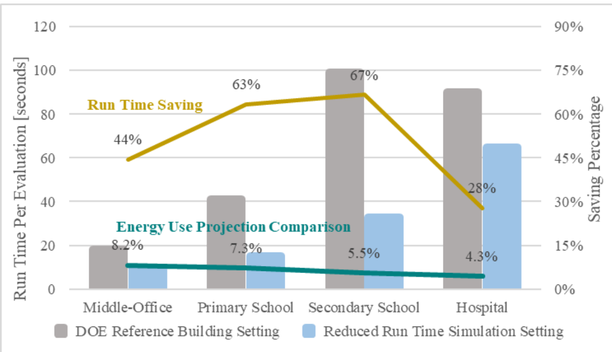

Figure 2: Comparison of savings in EnergyPlus run time and building energy use projection using proposed simulation parameter settings against DOE reference building parameters for four building use types

Figure 3 shows that 4 retrofit scenarios executed concurrently reduced the run time by 47 to 62% and more complex buildings (secondary school and hospital) achieved higher run time savings through parallel simulation.

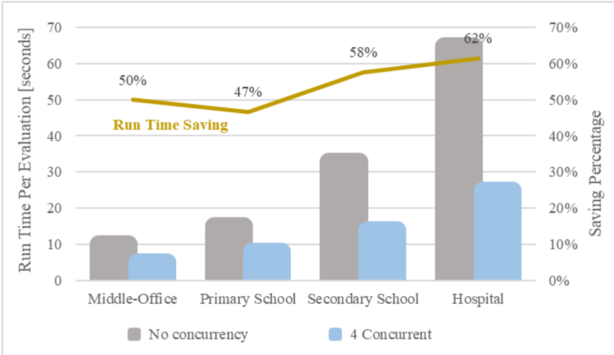

Figure 3: Comparison of savings in EnergyPlus run time when executing 4 concurrent simulations against no concurrency for four building use types

Reviewing the connection processes of the EnergyPlus and DAKOTA coupling using the log files resulted in finetuning and code improvement. It was discovered the lengthiest point of communication between EnergyPlus and DAKOTA is when new retrofitted building designs are pushed to EnergyPlus for simulation (step 5 to 6, Figure 2), which happens in every loop. This communication was then minimized to once for every population to save time and reduce the risk of the process breaking.

Lastly, different values of MOGA parameters of fitness assessor and selection operator were tested. The default and improved parameter values are presented in Table 4. Figure 4 shows two example buildings retrofit optimization results using the improved MOGA settings. The Pareto front and discarded solutions of the sample run are presented over the available points on the design space from other runs of the same building. The Pareto front for the primary school and hospital were achieved after 102 and 197 evaluations, respectively. In both cases, although the full range of possible solutions was not identified, the results were considered acceptable considering the distance of the predicted Pareto and the true Pareto front.

Table 4: Default versus improved MOGA fitness assessor and selection operator settings in DAKOTA

MOGA Parameters	Defaults	Improved Setting
max_function_evaluations	100	300
population_size (*initial population*)	50	20
crossover_type num_offspring num_parents	shuffle_random 2 2	shuffle_random 2 4
crossover_rate	0.8	0.8
mutation_type mutation_rate	replace_uniform 0.1	replace_uniform 0.1
replacement_type below_limit shrinkage_fraction	6 0.9	3 0.7
Convergence_type percent_change num_generations	Average_fitness_tracker	metric_tracker 0.05 3

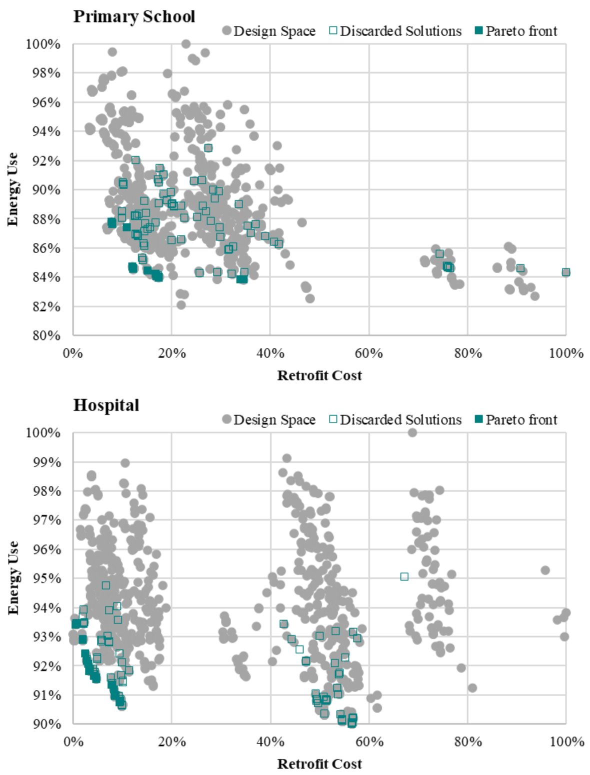

Figure 4: Example improved algorithm run for primary school and hospital buildings

Conclusion

The purpose of this paper is to describe the efforts made towards the development of a building retrofit optimization tool with a focus on improving the evaluation time to accommodate the large scale and more complex assessments. In order to reduce the total run time of the retrofit optimization tool several solutions were explored. This study provides an overview of the approach followed in choosing a suitable optimization algorithm and tool, as well as the methods used to link the optimization tool (DAKOTA), dynamic simulator (EnergyPlus), cost calculator, costed retrofit database, and minimum regulatory performance requirement considerations.

This paper is limited to the lessons learned in the initial stages of the tool development, which will be further improved, considering the KPI introduced. Advanced sampling techniques will be explored to perform an initial sensitivity analysis and design space exploration, and then create and import the first population members to MOGA.

Furthermore, this work will continue with expanding the costed-retrofit options library and the associated integration process, objective functions, constraints, number and types of buildings, and climatic conditions. The retrofit filtering engine will be improved to integrate user-defined constraints, such as limits on retrofit choices, total cost, and renovation objectives. These are essential to a user-centric product that can produce useful and reliable custom solutions.

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