

Aerodynamic Shape Optimization for High-Rise Conceptual Design

Integrating and validating parametric design, (fast) fluid dynamics, structural analysis and optimization

Ran Zhang¹, Christoph Waibel², Thomas Wortmann³

^{1,3}Xi'an Jiaotong-Liverpool University ²ETH Zürich

¹ran.zhang18@student.xjtlu.edu.cn ²waibel@arch.ethz.ch ³thomas.wortmann@xjtlu.edu.cn

Using an integrated workflow with parametric design, Computational Fluid Dynamic (CFD) and Fast Fluid Dynamic (FFD) simulations, structural analysis and optimization, this paper evaluates the relative suitability of CFD and FFD simulations for Aerodynamic Shape Optimization (ASO). Specifically, it applies RBFOpt, a model-based optimization algorithm, to the ASO of a supertall high-rise. The paper evaluates the accuracy of the CFD and FFD simulations relative to a slower, more exact CFD simulation, and the performance of the model-based optimization algorithm relative to CMA-ES, an evolutionary algorithm. We conclude that FFD is useful for relative comparisons, such as for optimization, but less accurate than CFD in terms of absolute quantities. Although results tend to be similar, CMA-ES performs less well than RBFOpt for both large and small numbers of simulations, and for both CFD and FFD. RBFOpt with FFD emerges as the most suitable method for conceptual design, as it is much faster and only slightly less effective than RBFOpt with CFD.

Keywords: Aerodynamic Shape Optimization, Computational Fluid Dynamics (CFD), Fast Fluid Dynamics (FFD), Model-based Optimization, High-rise Conceptual Design

INTRODUCTION

Simulation-based optimization is an increasingly popular computational method for designing more resource- and energy-efficient buildings. Computational designers combine parametric models with structural and environmental simulations to automatically find well-performing design candidates

and to inform further iterations in design processes. Recent research has investigated the efficiency of single-objective algorithms when paired with structural, building energy, and daylight simulations (Waibel et al. 2019; Wortmann 2019). This research shows that, the popular genetic algorithms (GAs) often are much less efficient than other al-

gorithms, for example model-based ones. Model-based algorithms create and refine surrogate models (i.e., fast-to-compute low fidelity approximations of high-fidelity simulations) during optimization processes, and thus can find well-performing designs much more efficiently.

This paper uses RBFOpt (Costa and Nannicini 2018), a model-based optimization algorithm, to optimize the aerodynamic shape of a high-rise in Shanghai to reduce wind loads. To the knowledge of the authors, model-based algorithms have so far only been applied to aerodynamic shape optimization (ASO) in the context of airplane wing design (Bartoli et al. 2019). RBFOpt has been developed specifically for the optimization of black-box optimization problems with expensive (e.g. time intensive) evaluation, of which ASO is a prime example. ASO can significantly reduce wind loads, and thus the structural requirements, for high-rises. But the particularly long run-times of computational fluid dynamics (CFD) simulations have so far not allowed the application of optimization algorithms that require hundreds or thousands of steps to find good solutions, such as GAs. Prior work in ASO for tall building design has either used GAs and simplified CFD simulations - so called fast fluid dynamic simulation (FFD) - or used manual "optimization".

Using an integrated workflow with parametric design, CFD and FFD simulations, structural analysis and optimization, this paper presents an evaluation of the relative suitability of CFD and FFD simulations for ASO, and then, to the knowledge of the authors, first application of a model-based optimization algorithm to the ASO of high-rises. The paper evaluates the accuracy of CFD and FFD simulations relative to a longer, more exact CFD simulation, and the performance of the model-based optimization algorithm relative to an evolutionary one. The paper thus demonstrates the viability of model-based optimization for ASO of high-rises and quantifies the potential benefits of this approach.

BACKGROUND

ASO is a relatively recent topic of research, which has been enabled through advances in both hardware and software.

Aerodynamic shape optimization with computational fluid dynamics

CFD simulations describe the flow of fluids, heat and concentrations of species (e.g. pollutants) within an enclosure based on conservation equations of mass and energy (Anderson 1995). These physical quantities are described as partial differential equations (PDEs), since the enclosure (also: domain) is discretized into finite volumes or finite elements. For many building engineering applications of CFD, turbulence modelling is essential, with the standard $\kappa - \epsilon$ model being the most common. Numerically, the PDEs are solved with iterative approximation methods, which explains the high computational cost of CFD approaches.

Malkawi et al. (2003) present an early example of optimizing a CFD model with a genetic algorithm (GA). However, the example geometry is a relatively simple, rectangular box. This simplicity likely is due to time-constraints relative to the available hardware. Chang (2013) manually "optimizes" the aerodynamic performance of high-rise geometries by qualitatively evaluating several different shapes and selecting the promising ones for CFD analysis, presumably because using a standard optimization algorithm, such as a GA, would require too many CFD simulations, and thus too much time. Liu et al. (2018) use a GA to optimize environmental comfort in terms of daylight and wind. They test five different urban morphologies in nine districts with a windspeed of 4m/s. This windspeed is much lower than the ones used for aerodynamic shape optimization (ASO). They state that the long time required for the CFD simulations reduces the optimization's effectiveness. Bartoli et al. (2019) presents the application of a global, model-based optimization algorithm to aerodynamic wing design. Model-based algorithms are designed for applications with time-intensive func-

tion evaluations such as CFD simulations (Holmström et al. 2008). This paper applies a similar algorithm, RBFOpt (Costa and Nannicini 2014) in an architectural context, specifically to the ASO of a high-rise.

Aerodynamic shape optimization with fast fluid dynamics

Fast Fluid Dynamics (FFD) can be understood as a simplified CFD simulation with faster solving time but lower model fidelity. It was originally intended for computer visualization, where the impression of physics, alongside solver stability and efficiency, are more important than physical correctness (Stam 1999). Since its introduction, several studies have investigated the applicability of FFD to building design (Zuo and Chen 2009; Jin et al. 2013). Chronis et al. (2011) combine a GA with FFD to optimize the shape of a canopy with 21 variables, because “through the use of less accurate but also computationally less demanding approaches, CFD simulations may be able to be applied . . . at earlier design stages”. They run tens of thousands of simulations in their experiments, which would be infeasible with CFD, but do not perform an accuracy comparison with CFD. Similarly, Waibel (2012) combines a Simulated Annealing algorithm with FFD to improve the ventilation effectiveness of wind cowls. Waibel et. al (2017) present an implementation of FFD for Grasshopper, a popular platform for parametric design, simulation and optimization, to allow optimization in conceptual design phases. They compare the accuracy of CFD and FFD and achieve good results for “simple validation cases” but confirm that “FFD has low accuracy in predicting velocity distributions in the wake regions behind obstacles”. In summary, FFD seems well suited for transient indoor flows, but requires care when used it for turbulent cases with high Reynolds Numbers, such as flow around buildings. But FFD is very suitable as an early-stage design tool, as the conclusions drawn from using FFD are generally pointing towards the right direction. Through a comparison with CFD, this paper aims to evaluate the suitability of FFD for ASO of high-rises in conceptual design phases.

Integrating aerodynamic shape optimization with structural analysis

Estrado (2019) presents an ASO workflow in Grasshopper that also integrates structural analysis. Like this paper, he uses the open source Butterfly (Sadeghipour Roudsari 2019) for CFD simulations with the open source CFD toolbox OpenFOAM (2019), Karamba (Preisinger 2019) for structural analysis and Opossum (Wortmann 2016) for optimization with RBFOpt. He considers using FFD, but ultimately chooses CFD due to the former’s lower accuracy, especially for complex geometries. He suspects the difference in accuracy between the two simulators results from different meshing techniques. This paper combines parametric modelling, wind simulations and structural analysis for an integrated ASO process. It extends existing studies with a performance comparison of two optimization algorithms (the model-based RBFOpt and the evolutionary CMA-ES (Hansen and Ostermeier 2001)) and two different simulation models (CFD and FFD) in terms of effectiveness and accuracy, respectively.

METHODOLOGY

To test the performance of the two optimization algorithms and the accuracy of the two simulators, we employ a workflow that integrates parametric modelling, CFD and FFD simulations, structural analysis and optimization in Grasshopper. We use Grasshopper, the visual programming environment of the 3D modelling software Rhinoceros, because (1) the availability of (mostly free) analysis and optimization tools, (2) the openness of its software development toolkit, which has allowed the authors to develop their own FFD and optimization plug-ins for it, and (3) it’s popularity among architectural designers, which ensures the practical relevance of this study.

Parametric model

We use a 300-meter, supertall high-rise in Shanghai as a test case. The site is near an old industrial water works in Shanghai that awaits redevelopment. In China, many high-rises have been designed

and constructed in the past decade, which underlines the need for more efficient high-rise designs. For simplicity, we assume that the high-rise contains only offices, with 75 floors and a consistent floor-to-floor height of four meter. The tower is radially symmetric. Seven horizontal control polygons, which are spaced equally along the tower's height, parametrically control the tower's shape (see figure 1). These control polygons are hexadecagons, i.e., regular, sixteen-sided polygons. Their radii can vary between 10 and 20 meters, resulting in hexadecagons with edge lengths between 3.9 and 7.8 meters. These edge lengths are suitable for the structural system, which consists of floor slabs held by a central core and a ring of external, inclined columns.

The model interpolates the roof's and floors' shapes between the control polygons, yielding 76 hexadecagons with varying radii. Since the hexadecagons' vertices are aligned, connecting corresponding vertices in order of height (i.e., the first vertex of all polygons, the second vertex of all polygons, etc.) yields inclined columns, and - when also connecting neighboring pairs of vertices - trapezoids, which define the tower's climate enclosure. For the fluid dynamics simulations, the model combines these trapezoids into a single quad mesh. We scale the resulting design candidates to have a constant gross area of around 50,000 square meters.

In summary, the parametric model has seven continuous variables that control the tower's shape.

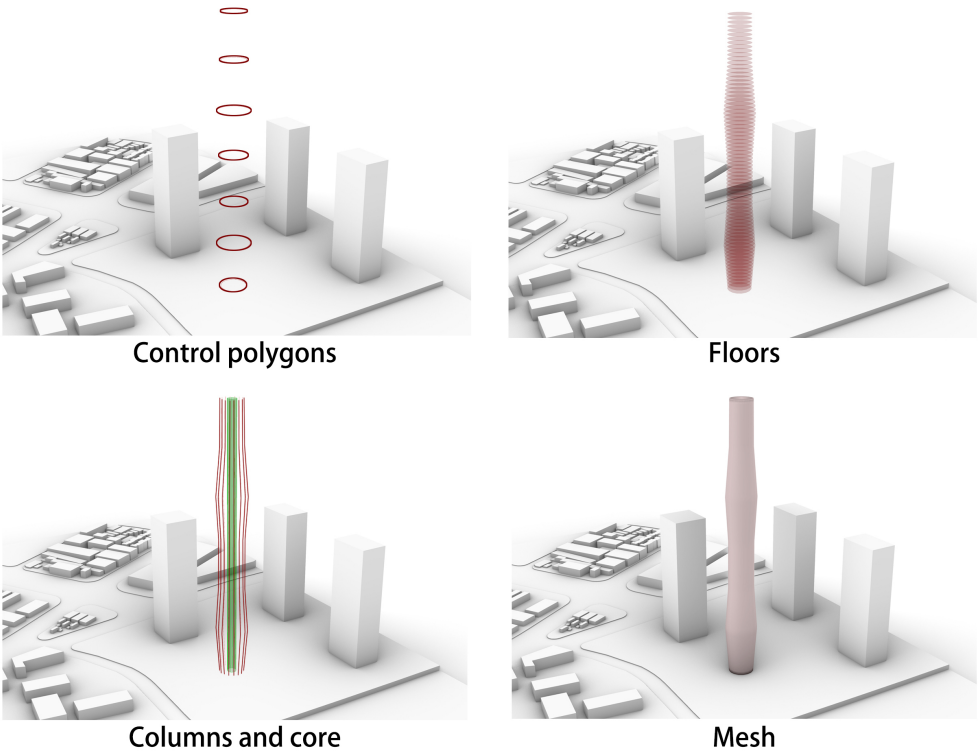


Figure 1
Generation steps of
the parametric
model.

The model produces (1) a fluid dynamics model consisting of a single quad mesh and (2) a structural model consisting of horizontal polylines that define the slabs' outlines and vertical polylines that define the external columns. This output of different types of geometry from the same model allows us to integrate different kinds of simulations into a single optimization workflow.

CFD simulations

For the CFD simulations, we use a domain of 5500 x 3000 x 1500m (X, Y, Z) with a cell size of 5m. Since, at the time of writing, we are not able to delineate between various periods of wind measurements (3-second gust, 10minute mean, mean hourly etc.), we adjusted the input wind speed to provide the desired wind pressure response. We set a wind speed of 35m/s at 10m above ground to produce a realistic static equivalent normal windward pressure of around 5KPa at the three-quarter height of the tower. This approach ensures realistic results through a reasonable weightage between lateral and gravity loads.

With an Intel Xeon CPU E5-2660 v2 with 2.20GHz and ten threads, a single simulation with CFD takes an average of 27 minutes to construct the wind tunnel, prepare the analysis mesh and to solve the resulting case, even when we calculate just 50 simulation iterations. For early design stages, this computational cost may be prohibitive. We use 50 simulation iterations during the optimization and validate the final results with a more accurate, but much slower, CFD simulation with 600 iterations. We use the default turbulence model in Butterfly for steady incompressible flows, RNG k-epsilon (Yakhot et al. 1992).

FFD simulations

We use an FFD plugin for Grasshopper that links to an open-source C# library (Waibel et al. 2017). We use a domain of 350 x 200 x 400m (X, Y, Z) with a cell size of 5m in a regular Cartesian grid. The inflow profile is the same as in Butterfly, with a surface roughness of 1.0 m and a wind speed of 35m/s at 10m above ground. Other settings used in our FFD simulations

are: 1.511×10^{-5} kinematic viscosity, 1×10^{-4} tolerance and maximal 10 iterations for the Jacobi solver, and 2nd order back-tracing. The simulation horizon is 30 with $dt=0.5$, resulting in 59 iterations. We use the average pressure values of the last five iterations as our simulation result. Figure 2 shows the convergence of the average p, u, v and w residuals for an FFD simulation of the case study. An average simulation of our high-rise model takes about four minutes. This FFD implementation (as most others) employs a rectangular grid for the analysis mesh. Therefore, reading values from curved surfaces such as the case study in this paper inherently introduces errors (see figure 3). But, despite the lower accuracy of FFD relative to CFD, the fact that its speed enables more optimization steps makes it potentially very relevant for ASO.

Figure 2
Residuals of an FFD
simulation of the
case study.

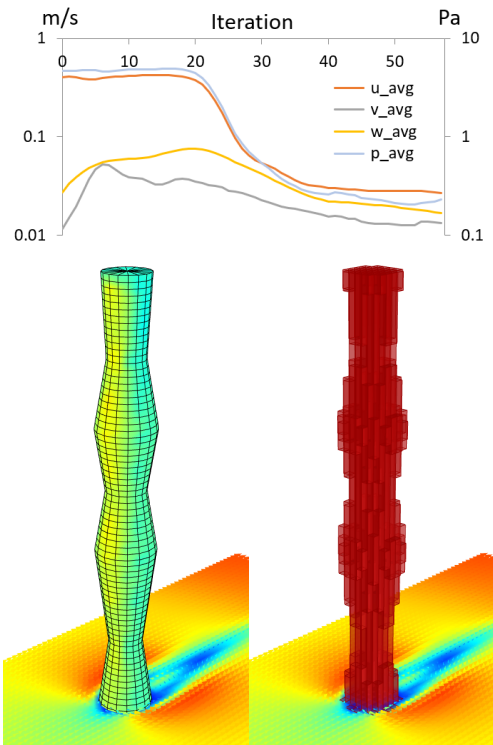
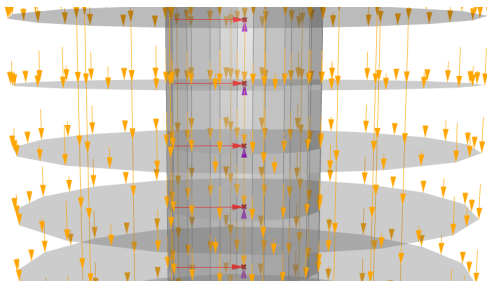


Figure 3
Original mesh (left)
vs Geometry
discretization in
FFD (right).

Structural analysis

We use Karamba, a Grasshopper plugin, for structural analysis. Karamba enables the optimization to be conducted within the Grasshopper environment. Karamba is no replacement for code-based structural analysis software, but offers a quick and efficient means to calculate the relative benefits of different design candidates in engineering practice. The structural model is based on the same parametric model used to define the shape for ASO. The radially-arranged, inclined columns (sixteen per floor), floor slabs and core provide a realistic structural frame as the basis of the optimization. The RC floor slabs' thickness is 30cm and the round columns' diameter 150cm. The unchanging RC core has a diameter of 10 meters and a wall thickness of 100cm.

We apply three gravity loads to the floor slabs: (1) Self-weight, (2) a superimposed dead load of 2.5KPa to represent a reasonably lightweight office configuration and (3) a live load of 2.5KPa. We apply the results from CFD or FFD as wind loads- specifically, horizontal force and torsion - to the diaphragm centers of the floors (see figure 4). Since the tower is rotationally symmetric, it suffices to consider only one wind direction. (Because wind from different directions affects the tower's structure equally.) Following Eurocode, we combine gravity and wind load cases into seven load combinations that are applied to each design candidate. For optimization, we evaluate the design candidates according to the worst displacement resulting from the seven load combinations.



Optimization methodology

Since the CFD simulations take about seven times longer than the FFD simulations, we budget 100 function evaluations, i.e., simulations, for optimization with CFD, and 1,000 function evaluations for optimization with FFD. We use the two best-performing optimization algorithms from an extensive benchmark on building energy problems: RBFOpt and CMA-ES (Waibel et al. 2019). In this benchmark, RBFOpt was the best-performing algorithm for small function evaluation budgets (i.e., numbers of simulations), and CMA-ES the best-performing one for large budgets. RBFOpt and CMA-ES also were the most robust algorithms. We perform only a single run per algorithm, but the algorithm's robustness provides a measure of confidence in the optimization results. Both algorithms are available in Opossum for Grasshopper (Wortmann 2017).

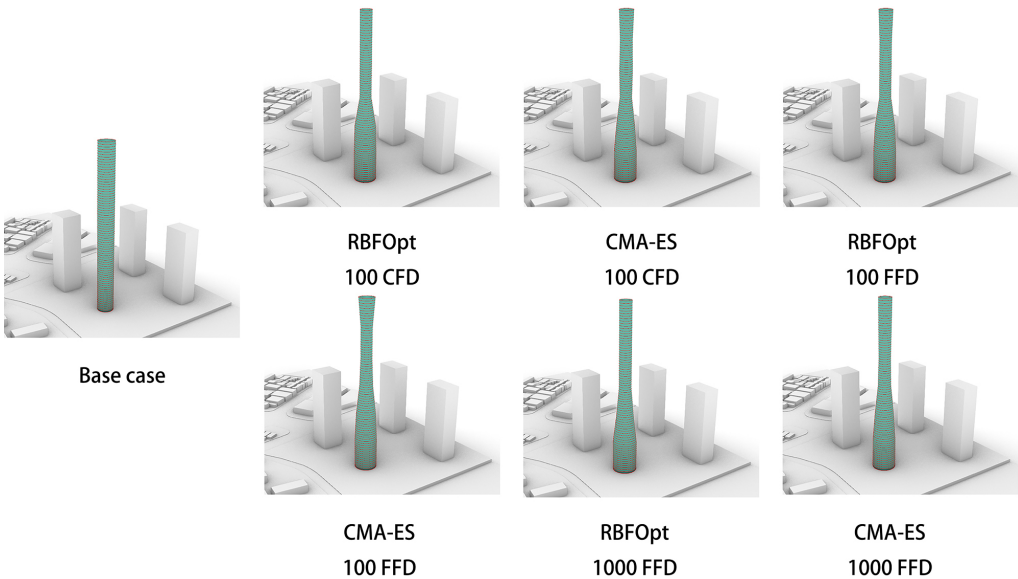
RESULTS

To evaluate the performance of the RBFOpt and CMA-ES algorithms, as well as the relative accuracy of the CFD and FFD simulations, we analyze the best results from a single run of six ASO methods: 100 function evaluations for CFD (RBFOpt 100 CFD and CMA-ES 100 CFD) and FFD (RBFOpt 100 FFD and CMA-ES 100 FFD) and after 1,000 function evaluations for FFD (RBFOpt 1000 FFD and CMA-ES 1000 FFD). We compare these results to the base case of a cylindrical tower (see table 1 and figure 5). To evaluate the performance of the CFD and FFD simulations, we retest the best result from each run with a much longer CFD simulation with 600 iterations.

All six optimized solutions are similarly bottle-shaped, which minor variations in the bottles' "necks" (see figure 5). The resulting pressures and displacement are similar as well. But, in comparison with the base case, these pressures and displacements are reduced by up to 67% (see table 1). Of the two tested algorithms, RBFOpt is better for both simulators and function evaluation budgets. For example, the maximum displacement of RBFOpt 100 FFD is better than the results from CMA-ES 100 FFD and CMA-ES 1000

Figure 4
Screenshot of the structural model. Gravity loads in orange and wind loads in red and purple.

Figure 5
The best results of
the six ASO
methods.



FFD. These results show the effectiveness and efficiency of model-based optimization for ASO.

For both RBFOpt and CMA-ES, 100 optimization steps with CFD took about 45 hours, but only about 6 hours for FFD. 1,000 optimization steps with FFD took about 60 hours (see table 1). But the variable values, resulting shapes (see figure 5) and simulation results from 100 optimization steps with FFD are quite similar to the others and result in similarly low displacements (see table 1). As such, RBFOpt 100 FFD seems the best method for conceptual design.

When retesting the optimization results with more accurate CFD simulations (with 600 instead of 50 iterations), the differences between the methods increase, and 100 optimization steps with CFD becomes relatively better (see table 1). Note that the displacements from the more accurate CFD simulation are about twice the displacements from FFD and the less accurate CFD simulations. In other words, CFD with low accuracy and FFD can serve as effective guides for optimization, but simulation results

should be understood only relatively and not as absolute quantities. Based on the more accurate CFD results, CFD RBFOpt 100 is the best solution, but RBFOpt FFD 100 is only 1% worse and about eight times faster. As such, based on these results, RBFOpt FFD 100 is the best ASO method for concept design.

CONCLUSION

This paper presents an integrated ASO workflow of parametric design, wind simulations, structural simulation and optimization. It shows that CFD and FFD simulations can serve as effective guides for optimization. Although both the CFD and FFD simulations used for optimization systematically underestimated pressure values, ASO resulted in up to 67% percent reductions of maximum displacements. The solutions from all optimization runs were similar for both optimization algorithms (RBFOpt and CMA-ES), simulation models (CFD and FFD) and for 100 and 1,000 function evaluations. But the model-based RB-

	Base Case	RBFOpt 100	CMA-ES 100	RBFOpt 100	CMA-ES 100	RBFOpt 1000	CMA-ES 1000 FFD
		CFD	CFD	FFD	FFD	FFD	
Variable Values (m)							
Radius 1	10	19.96	19.72	19.98	19.86	20.00	19.96
Radius 2	10	19.98	19.49	19.96	19.98	19.99	19.57
Radius 3	10	18.76	15.90	17.48	17.64	14.48	16.20
Radius 4	10	10.01	10.03	10.01	11.77	10.01	10.93
Radius 5	10	10.06	10.86	10.00	10.00	10.01	10.00
Radius 6	10	10.01	10.05	10.00	10.05	10.00	10.61
Radius 7	10	10.11	11.67	11.66	13.96	10.01	10.95
Runtime (min)							
	N/A	2582	2768	344	347	3428	3715
Pressure CFD (kPa)							
Minimum	-0.61	-0.66	-0.79	-0.75	-0.39	-0.94	-0.64
Average	2.04	1.96	1.91	1.91	1.96	1.91	1.92
Maximum	4.21	4.11	4.16	4.12	4.24	4.22	4.14
Pressure FFD (kPa)							
Minimum	-0.94	-0.84	-1.02	-1.07	-1.05	-0.94	-0.96
Average	-0.06	-0.13	-0.10	-0.17	-0.21	-0.19	-0.11
Maximum	0.90	0.78	0.89	0.85	0.87	0.76	0.87
Displacement CFD (cm)							
Minimum	8.77	6.97	7.14	7.05	7.36	6.96	7.09
Average	41.39	14.91	16.50	15.61	16.57	15.39	16.02
Maximum	65.40	21.05	23.66	22.20	23.64	21.97	22.87
Displacement FFD (cm)							
Minimum	8.77	6.97	7.14	7.05	7.36	6.96	7.09
Average	49.32	17.34	19.59	18.31	20.74	17.42	18.72
Maximum	79.02	25.25	29.01	26.86	30.84	25.38	27.54
Pressure CFD accurate (kPa)							
Minimum	-5.29	-6.20	-5.68	-5.78	-6.27	-6.73	-5.71
Average	-0.43	-0.44	-0.42	-0.45	-0.42	-0.47	-0.42
Maximum	4.89	5.05	5.05	5.11	5.17	5.27	5.16
Displacement CFD accurate (cm)							
Minimum	8.77	6.97	7.14	7.05	7.36	6.96	7.09
Average	81.89	28.29	32.25	30.35	32.23	32.98	31.07
Maximum	135.07	44.11	50.81	47.60	50.63	52.19	48.81

Table 1
Variable values,
runtimes and
simulation results
for the base case
and the best results
of the six ASO
methods.

FOpt in combination with 100 FFD simulations is the fastest ASO method for concept design, and only 1% worse than the best solution, which was found by RBF-FOpt with 100 CFD simulations. ASO with RBF-FOpt and FFD yields results in hours rather than days and thus holds great promise to improve the sustainability of future high-rises by reducing the amount of materials required for lateral stability already during concept design. Future research will further examine the relative accuracy of CFD and FFD, for example by tuning the FFD model with CFD results, test optimization with asymmetric tower geometries and different wind directions, and provide more extensive benchmark results from more algorithms and runs.

ACKNOWLEDGMENT

We thank Robert Bamford and Nguyen Minh Chau from Web Structures, Singapore for their advice on integrating the CFD results with the structural system.

REFERENCES

- Anderson, J 1995, *Computational Fluid Dynamics*, McGraw-Hill Education, New York, NY
- Bartoli, N, Lefebvre, T, Dubreuil, S, Olivanti, R, Priem, R, Bons, N, Martins, J and Morlier, J 2019, 'Adaptive modeling strategy for constrained global optimization with application to aerodynamic wing design', *Aerospace Science and Technology*, 90, pp. 85-102
- Chang, D 2013 'Aerodynamic Performance Driven Form-Generation for Skyscraper Design', *Proceedings of CAAD Futures*, Berlin, Heidelberg, pp. 315-326
- Chronis, A, Turner, A and Tsigkari, M 2011 'Generative Fluid Dynamics: Integration of Fast Fluid Dynamics and Genetic Algorithms for Wind Loading Optimization of a Free Form Surface', *Proceedings of the 2011 Symposium on Simulation for Architecture and Urban Design*, San Diego, CA, pp. 29-36
- Costa, A and Nannicini, G 2018, 'RBF-Opt: an open-source library for black-box optimization with costly function evaluations', *Mathematical Programming Computation*, 10(4), pp. 597-629
- Estrado, E 2019, *Optimisation of complex geometry buildings based on wind load analysis*, Master's Thesis, Delft University of Technology
- Hansen, N and Ostermeier, A 2001, 'Completely de-randomized self-adaptation in evolution strategies', *Evolutionary computation*, 9(2), pp. 159-195
- Holmström, K 2008, 'An adaptive radial basis algorithm (ARBF) for expensive black-box global optimization', *Journal of Global Optimization*, 41(3), pp. 447-464
- Jin, M, Zuo, W and Chen, Q 2013, 'Simulating Natural Ventilation in and Around Buildings by Fast Fluid Dynamics', *Numerical Heat Transfer, Part A: Applications*, 64(4), pp. 273-289
- Liu, Y, Gang, Y and Xu, X 2018, 'The Automatic Optimizing Method of Morphological and Microclimatic Environmental Performance Based on Genetic Algorithm', *Chinese and Overseas Architecture*, 6, p. 71
- Malkawi, AM, Srinivasan, RS, Yi, YK and Choudhary, R 2003 'Performance-based Design Evolution: The Use of Genetic Algorithms And CFD', *Building Simulation 2003*, Eindhoven, NL, pp. 793-798
- Stam, J 1999 'Stable Fluids', *Proceedings of the 26th Annual Conference on Computer Graphics and Interactive Techniques*, pp. 121-128
- Waibel, C 2012 'Non-deterministic Shape Optimisation of Wind Cows by applying Simulated Annealing and Fast Fluid Dynamics', *Proceedings of 2nd Conference: People and Buildings*, London, UK, p. 7
- Waibel, C, Bystricky, L and Kubilay, A 2017 'Validation of Grasshopper-based Fast Fluid Dynamics for Air Flow around Buildings in Early Design Stage', *Proceedings of the 15th International Conference of IBPSA*, San Francisco, CA
- Waibel, C, Wortmann, T, Evins, R and Carmeliet, J 2019, 'Building energy optimization: An extensive benchmark of global search algorithms', *Energy and Buildings*, 187, pp. 218-240
- Wortmann, T 2017 'Opossum—Introducing and Evaluating a Model-based Optimization Tool for Grasshopper', *Proceedings of the 22nd CAADRIA Conference*, Hong Kong, CN, pp. 283-292
- Wortmann, T 2019, 'Genetic Evolution vs. Function Approximation: Benchmarking Algorithms for Architectural Design Optimization', *Journal of Computational Design and Engineering*, 6(3), pp. 414-428
- Yakhot, V, Orszag, SA, Thangam, S, Gatski, TB and Speziale, CG 1992, 'Development of turbulence models for shear flows by a double expansion technique', *Physics of Fluids A: Fluid Dynamics*, 4(7), pp. 1510-1520
- Zuo, W and Chen, Q 2009, 'Real-time or faster-than-real-time simulation of airflow in buildings', *Indoor Air*, 19(1), pp. 33-44
- [1] github.com/ladybug-tools/butterfly/wiki
- [2] www.openfoam.org
- [3] www.karamba3d.com