Optimization of urban geometry to minimize the effect of automotive pollution

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Abstract

The paper addresses the optimization of an idealized urban geometry, as defined by building height and street width, to minimize the effect of automotive pollution as evidenced by CO concentration levels. There is an increasing interest in the contribution of automotive pollution to urban air pollution. The formulation of building regulations, as well as the optimization of proposed street-use patterns, require modeling studies of the pollutant dispersion due to automotive emissions. The dispersion is closely linked to the geometrical features and meteorology of the urban environment. This paper uses the techniques of Computational Fluid Dynamics (CFD) to calculate the dispersion of CO emitted by traffic in a section of an urban environment. This modeling technique is then linked to mathematical optimization to optimize the geometry (building height and street width) for the worst case scenario of wind speed and direction (as also determined using mathematical optimization techniques). The optimization process is performed using the DYNAMIC-Q method of Snyman. The results show that the method has great potential in the application to real and more complex urban geometry for the minimization of the effect of automotive pollution.

1 Introduction

There is an increasing interest in the contribution of automotive pollution sources to urban air pollution. This is mainly due to the large proportion of urban pollution due to transport-related sources. E.g., in Greater London and Berlin in 1993, the carbon monoxide (CO) from road transport sources contributed to approximately 57% of the total CO budget for these cities (Sieka et al[1]).
Extensive emission inventory studies are being performed worldwide to quantify the sources due to road transport. The modeling of the impact of automotive pollutants has also been receiving increased attention (e.g. Albergel and Jasmin[2], Sini et al[3]). Included in this modeling, is the determination of the flow patterns in urban geometry due to local effects as well as meso-scale meteorological conditions. With ever-increasing computer power, Computational Fluid Dynamics (CFD) techniques have been increasingly applied to the simulation of atmospheric problems.

For the design of regulations to govern new developments and changes to existing urban environments, advance simulation of conditions is required. This typically leads to a design problem with many design variables. Amongst these variables are traffic flow parameters (speed, direction, type of vehicles, age of fleet, etc.), street canyon depth and width (linked to building height restrictions), and street spacing and orientation, to name a few. CFD can play an important role in the analysis of the impact of automotive pollution on urban pollution levels and distribution. However, one can imagine that an extensive parametric variation of the design variables mentioned would result in an impractical situation as far as the required computing overheads are concerned.

A more efficient approach, that has until recently been too expensive, is to combine CFD with mathematical optimization, to provide optimum solutions that automatically take the cross-influence of the variables into account. This approach has recently been applied by the authors to the minimization of air pollution due to stacks [4]. This approach is similar to treating the analyses as part of a design optimization problem, where an objective function (e.g. automotive emission CO level) is minimized for certain design variables (e.g. street width, building height, etc.) and an array of wind speed and direction (obtained from meteorological data). In this study, the commercial CFD code, STAR-CD[5], is linked to the DYNAMIC-Q algorithm of Snyman et al[6-8], which is a gradient method for constrained optimization. Apart from Ref. 4, this approach has also been demonstrated for grid optimization of separated flow geometries [9], turbulence modeling for high-lift airfoils [10], and the optimization of heat sinks in electronic enclosures [11].

The next section will define the optimization problem, whereafter the theoretical modeling employed will be described. This includes the CFD and mathematical optimization modeling. This is followed by results and discussion, with conclusions made from the results concluding the paper.

2 Problem definition and formulation

The urban automotive air pollution optimization problem considered in this study is depicted graphically in Figure 1. Shown is a 3x3 array of buildings with two streets in each of the two main directions. The buildings are assumed to be square-shaped when viewed from above, and the streets are assumed to have a constant width with uniform spacing. The design variables considered as a first
step are street width and building height. The size of the urban section considered (500m by 500m) remains constant for this initial study.

CO is used as a representative automotive emission since it is relatively stable, easily measured and comes mainly from vehicular emissions. CO has also been used as proxy for other pollutants, including NO\textsubscript{x}, hydrocarbons and PM\textsubscript{10} [12]. The CO values due to vehicles range from 1 g/km (Samaras et al[13]) for cars running hot with catalytic converters, to 80 g/km (Spadaro et al[14]) for conventional cars without converters in cold-start short distance cycles. In typical rush-hour conditions, there is a mix in the type of vehicles present in the fleet. Albergel and Jasmin [2] use emissions based on INRETS and CORINAIR reports for passenger cars and light duty vehicles in evening rush-hour traffic at 7.3km/h. The CO value they derive from these reports is 30.57mg/s, resulting in about 60 g/km for a 4-lane avenue. A value of 15g/km CO emission per vehicle lane is used in this study as representative, but could easily be varied due to the method of implementation.

The two design variables are shown in Figure 1. \( x_1 \) is the street width and \( x_2 \) is the building height. The wind profile is assumed to follow a power law distribution. The wind direction and wind speed are allowed to vary continuously between specified limits, with the aim of finding the wind speed and direction that would produce the worst-case scenario as far as CO pollutant concentration level is considered, and then minimizing this level by varying the geometrical variables. Due to this complex problem, the optimization problem can be seen as a nested optimization problem. In this study, the wind is treated as steady state.
without gusting. In general, pollutant episodes with transient wind conditions can be considered if instantaneous pollutant levels are required. The current type of analysis is more suited for averaged or accumulative pollutant scenarios. Due to the symmetric lay-out of the urban geometry, the range of wind directions that needs to be considered is only one quarter of all wind directions, i.e. from 0° to 45° in Figure 1. The atmosphere is considered as neutrally stable in this study.

The complete mathematical formulation of the optimization problem, in which the constraints are written in the standard form \( g(x) \leq 0 \), where \( x \) denotes the vector of the design variables, is as follows:

\[
\begin{align*}
\min & \ f(x) = \max_{a,\alpha} Con(x) \\
\text{subject to} & \\
& g_j = -x_j + x_j^{\min} \leq 0; \ j = 1,2 \\
& g_{j+2} = x_j - x_j^{\max} \leq 0; \ j = 1,2
\end{align*}
\]

where the upper and lower limits on the variation of the variables are given by \( x_j^{\min} \) and \( x_j^{\max} \). \( \alpha \) is the wind direction anti-clockwise relative to North and \( V \) the wind speed in m.s\(^{-1}\). \( Con(x) \) is the maximum CO level obtained from a CFD simulation given a specific geometry (defined by \( x \)) at a 2-m level in the streets for a range of wind directions. The calculation of the objective function is therefore itself an optimization (maximization) problem in two variables, wind speed and wind direction, with limits on these variables acting as constraints. The numerical value of these constraints are given below in Table 1.

3 Theoretical modelling

3.1 CFD modelling

3.1.1 Grid generation
The grid is generated using algebraic grid generation techniques (transfinite interpolation and Vinokur stretching [15]) exterior to the CFD code. A new grid is generated for each perturbation of the design variables. The total flow domain in 5km by 5km square and 300m high. Grid sizes used varied from 200 000 to 300 000 cells.

3.1.2 Flow solver
The commercial CFD code, STAR-CD is used, as mentioned above. The Reynolds-Averaged Navier-Stokes equations are solved with turbulence closure provided by the standard k-\( \epsilon \) turbulence model. The SIMPLE algorithm was employed. The simulations were performed on an Aspen Durango with DEC Alpha 600MHz processor. When being the sole user on this machine, a run-time of approximately 0.15ms/grid point/iteration was achieved. This translates in each iteration (refer Figure 4 below) taking approximately 13 hours.
3.1.3 Flow solutions
To illustrate the type of solutions that are used in the optimization process, a representative case is given in Figure 2. Shown are the steady-state velocity vectors for an oblique wind condition of $\alpha = 20^\circ$. The vectors displayed are at the 2m-elevation. Note that the wind speed and direction in the street canyons differ from the prevailing wind. Of interest is the level of 'washing-out' that occurs in the streets due to the wind, as this impacts the dispersion of automotive emissions.

![Velocity vectors](image)

Figure 2: Velocity vectors. Wind direction, $\alpha = 20^\circ$; Wind speed, $V = 3\, \text{m.s}^{-1}$; CO source: 15g/km/lane; Design variables: $x_1 = 10\, \text{m}, x_2 = 15\, \text{m}$

3.1.4 CO concentrations
To illustrate the types of CO concentration distributions that are computed in the street canyons due to the types of wind distribution shown in Figure 2 above, CO concentration levels are shown at the 2m elevation in Figure 3. In Figure 3a), the wind direction is head on ($\alpha = 0^\circ$) while in Figure 3b), ($\alpha = 20^\circ$). Note the complex distribution of CO as exhibited by the close-ups of the street intersections. Note that the highest CO level of the two wind conditions shown occurs in the ($\alpha = 0^\circ$) case.
Figure 3a): CO concentration contours at 2m elevation. Wind direction, $\alpha = 0^\circ$;
Wind speed, $V = 3\text{m.s}^{-1}$; CO source: 15g/km/lane;
Design variables: $x_1 = 10\text{m}$, $x_2 = 15\text{m}$

Figure 3b): CO concentration contours at 2m elevation. Wind direction, $\alpha = 20^\circ$;
Wind speed, $V = 3\text{m.s}^{-1}$; CO source: 15g/km/lane;
Design variables: $x_1 = 10\text{m}$, $x_2 = 15\text{m}$
3.2 Mathematical optimization

3.2.1 Optimization algorithm
The reader is referred to Ref. 4 and 9-11 for the detail implementation of the optimization method used in this study. In essence, the DYNAMIC-Q method of Snyman et al.[8] involves the application of a dynamic trajectory method for unconstrained optimization [6,7], adapted to handle constrained problems through appropriate penalty function formulations [16-19]. This DYNAMIC method is applied to successive approximate Quadratic subproblems [8,20]. The successive subproblems are constructed from sampling, at relative high computational expense, the behavior of the objective function (described below) at successive approximate solution points in the design space. The subproblems, which are analytically simple, are solved quickly and economically using the adapted dynamic trajectory method.

3.2.2 Selection of objective function
The selection of the objective function deserves some mention. The allowable levels due to pollutant sources are determined by legislation and depend on the sources. For the current implementation, the mathematical nature of the pollutant distribution must also be taken into account. Possible alternatives are e.g. the maximum CO concentration level in the street canyon volume, the maximum level at a specified height (e.g. 2m), the integrated CO concentration level in the street canyon volume, or the integrated CO concentration level at the 2m height. Alternatively, the total CO emitted (kg) that remains in the street canyon volume can be used, preferably normalized by the street canyon volume for valid comparison for different street canyon parameters. The \( \text{Con}(x) \) used in the objective function (eqn. 1) is that of the maximum CO concentration level at the 2m elevation since it exhibited the most interesting variation with the design variables.

3.3 Combination of CFD and Mathematical Optimization

The combination is performed in the Unix environment using FORTRAN 90, which allows dynamic memory allocation and system calls. This integration of the CFD and mathematical optimization algorithm into one program allows an automated optimization process and a quick turnaround when formulating and implementing new optimization problems.

4 Results and Discussion

4.1 Design parameters
The solution parameters as well as the limits on the design variables used are given in Table 1.
Table 1: Parameters used for optimization and limits on design variables.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Limits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Street width (x_1) [m]</td>
<td>5-14</td>
</tr>
<tr>
<td>Building height (x_2) [m]</td>
<td>6-30</td>
</tr>
<tr>
<td>Wind direction (\alpha) [°]</td>
<td>0-45</td>
</tr>
<tr>
<td>Wind speed (V) [m.s(^{-1})]</td>
<td>2-5</td>
</tr>
<tr>
<td>Power law (z_0, n) [m, -]</td>
<td>10, 0.18</td>
</tr>
<tr>
<td>Schmidt number</td>
<td>0.77</td>
</tr>
<tr>
<td>Diffusivity ([m^2.s^{-1}])</td>
<td>2.02x10(^{-3})</td>
</tr>
</tbody>
</table>

4.2 Optimization results

The history of the objective function as well as the design variables is given in Figure 4.

Figure 4: History of CO concentration, wind speed and direction, and street width and building height. CO source: 15g/km/lane

Worst-case(1):
Iteration 4: Wind direction, \(\alpha = 17.319°\); Wind speed, \(V = 2.000\text{m.s}^{-1}\)
Optimized geometry: Iteration 9: \(x_1 = 12.213\text{m}, x_2 = 6.000\text{m}\)

Worst-case(2):
Iteration 13: Wind direction, \(\alpha = 5.569°\); Wind speed, \(V = 2.000\text{m.s}^{-1}\)

The optimization was not allowed to go to full convergence in the intermediate (nested) loop to speed up the overall convergence rate. Note that the wind speed is reduced to the minimum allowable for the worst-case meteorological condition (iteration 1 through 4), as expected, but that the worst wind angles of 17.319° and 5.569° for the two building height and street width configurations could not have been predicted by any other method. Given the first worst-case wind condition (iteration 4), the optimizer proceeded to reduce the building height and increase the street width (iteration 5 through 9) in order to reduce the maximum CO level at the 2m elevation. Surprisingly, the optimum obtained is not the lowest building and widest street width allowed, but the values shown in the figure caption. In the
final section shown in Figure 4, the optimizer again performs a maximization problem on the wind conditions with the building height and street width values obtained (iteration 10 through 13). With the lower buildings and wider streets of iteration 9, the maximum concentration at iteration 13 is lower than the first worst case (iteration 4), indicating that the optimizer is moving in the right direction. The process was terminated at this point due to a lack of computing time, but would typically carry on for a few more global iterations until convergence is obtained.

5 Conclusion

This study illustrated the combination of CFD and mathematical optimization to the minimization of the effect of automotive pollutants in urban environments. Although an idealized geometry was investigated, the method is readily extensible to more complex cases. The optimization algorithm proved to be robust with convergence to engineering accuracy obtained in under six iterations.

6 Future work

In future work, the method illustrated here will be extended to include the effects of traffic momentum (piston effect) as well as traffic-induced turbulence. In addition, the optimization will be applied to real urban environments. A surrogate problem that can be considered is that of maximizing building volume given a maximum pollutant level constraint to maximize building occupancy.

7 Acknowledgements

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References


