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A comparison between two metaheuristic optimization algorithms for downburst simulation

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SUMMARY:
Strong downbursts can produce surface winds that can threaten civil structures. From the wind engineering prospective, modelling and simulating such severe wind is therefore extremely important for structural safety and design wind speed evaluation. This study deals with downburst wind field reconstruction by means of an analytical model, developed previously by the authors, coupled with two metaheuristic algorithms, the Differential Evolution (DE) and the Teaching Learning Based Optimization (TLBO), for the evaluation of downburst kinematic and geometrical parameters. The optimization problem minimizes the relative error between recorded and simulated wind speed and direction time histories. A comparison is made between the performance of the two algorithms for ten thunderstorm downburst events measured in northwestern Italy between October 2011 and October 2015. Both algorithms provide solutions which are coherent with the downburst parameter values presented in literature. TLBO outperforms DE since it has a faster convergence rate toward the optimal solution.

Keywords: Downburst analytical model, metaheuristic algorithms, single-objective optimization, differential evolution, teaching-learning-based optimization, downburst kinematic parameters.

1. INTRODUCTION

The study of intense thunderstorm-related downburst winds and their actions and effects on structures has been a dominant topic of the research in the wind engineering community over the last forty years (Letchford et al., 2002). Thunderstorms are non-stationary phenomena at the mesoscale, which occur in convective conditions with velocity profiles substantially different from those that are typical of the atmospheric boundary layer (ABL). Design wind velocities with mean return periods greater than 10-20 years are often associated with such phenomena (Solari, 2014). The great complexity of downburst outflow winds requires, from the wind engineering perspective, the formulation of analytical and empirical models able to capture the main features of this phenomenon.

The current study investigates the reconstruction/simulation of downburst outflow winds using an analytical model developed by the authors (Xhelaj et al., 2020) which has been coupled in the current work with two global metaheuristic optimization algorithms, namely the Differential Evolution (DE) (Storn and Price, 1997) and the Teaching-Learning-Based Optimization (TLBO) (Rao et al., 2011). The procedure consists in the creation of an optimization problem which minimizes the relative error between anemometric measurements of downburst outflows and simulated time histories of downburst wind speed and direction. The minimizing solution, relative to a specific downburst case, consists in a set of 11 model parameters which are needed to reconstruct the geometrical and kinematical features of the downburst under consideration. The purpose of the minimization is the determination of the most accurate model's parameters. The algorithms are compared through the simulation of ten selected full-scale downburst events that occurred in the port area of La Spezia, Genoa and Livorno between October 2011 and October 2015. These time series were collected during the European Projects “Wind and Ports” (Solari et al., 2012) and “Wind Port and Sea” (Repetto et al., 2017; 2018). Only the 30 s moving average time series of the wind speed and direction are considered for the purpose of this study.

2. SIMULATION RESULTS AND COMPARISON OF DIFFERENTIAL EVOLUTION AND TEACHING LEARNING BASED OPTIMIZATION ALGORITHMS

The application of the DE and TLBO algorithms to the downburst model of Xhelaj et al. (2020) is performed through the definition of an optimization problem which represents a single-objective, nonlinear and bound constrained problem. The lower and the upper bound of the 11 parameters which ultimately identify the search space ($\Omega \subseteq \mathbb{R}^{11}$), are set according to values present in literature. Table 1 reports a brief description of the model parameters and their range of variation.

Table 1. Model parameter description and their variability (lower and upper bound)

Model parameters	Range of variation
Maximum radial velocity $V_{r,max}$ (m/s)	$0\ to\ 40$
Downdraft radius R (m)	$200\ to\ 2000$
Dimensionless radial distance from downburst center at which $V_{r,max}$ occurs: $\rho = \frac{R_{max}}{R}$ $(-)$	$1.6\ to\ 2.6$
Period of linear intensification T_{max} (min)	$2\ to\ 15$
Duration of the downburst event T_{end} (min)	$15\ to\ 45$
x-component touchdown location (at $t = 0$) x_{C0} (m)	$-10000\ to\ 10000$
y-component touchdown location (at $t = 0$) y_{C0} (m)	$-10000\ to\ 10000$
Downburst translational velocity V_t (m/s)	$0\ to\ 40$
Downburst translational direction α_t (deg)	$0\ to\ 359.9$
Low-level ABL wind speed V_b (m/s)	$0\ to\ 40$
Low-level ABL wind direction α_b (deg)	$0\ to\ 359.9$

The comparison between the algorithms is based on the performance of each algorithm in finding a “good” optimal solution, given the incomplete information provided by the objective function. The latter is defined as the relative error between the observed and the simulated 30 s moving average mean wind speed and direction. Since DE and TLBO are stochastic algorithms, they are run independently 256 time in order to achieve a best solution. The number of iterations for both the algorithms is set to $T = 500$. The comparison metrics are based on the best, mean and standard deviation (std) objective function value of the 256 independent runs that both algorithms reach after 500 iterations. The best objective function value represents the lowest value reached by a specific algorithm; the mean and the std objective function value after 500 iterations gives respectively an overall behavior of the performance and of the robustness of each algorithm.

Fig. 1 describes the performance of both algorithms for one of the 10 downburst cases occurred in the port area of Livorno on 4 October 2015. This case highlights some important features of the behavior of the objective function which are also found in the other nine remaining cases (not shown). Fig.1 (a) displays the “performance chart” which describes the convergence of the objective function, for both algorithms, as the number of iterations increases. The chart contains the upper and lower envelope of all the 256 independent runs for both the algorithms. At the end of 500 iterations, the value of the upper envelope coincides with the worst objective function value (worst solution) while the lower envelope coincides with the best objective function value (best solution). In the performance chart is also traced (dashed line) for both the algorithms the mean convergence curve. The analysis of the performance chart shows an important feature, which can be crucial for reducing the computational time for the application of the analytical model. The lower envelope curve associated with TLBO have lower values than the DE counterpart, except when they get closer to the maximum number of iterations. The TLBO lower envelope curve reach almost stable values after 50 iterations, which indicates that TLBO converges at a much faster rate than DE (almost 1 order of magnitude faster). Similar trend for the rate of convergence is achieved by the other 9 downburst events. In general, for the ten downburst cases, the algorithm that has better convergence value both in the best and mean solution is the TLBO. On the other hand, DE has lower std than TLBO for all the 10 cases, which indicates that DE is more robust than TLBO. Fig. 1 (b) shows, for the case of the Livorno downburst, the time history of the best simulation results (i.e., the one that produce the lowest objective function value), in terms of the moving average mean wind speed (top) and direction (bottom) for both the algorithms, compared to the recorded data. The figure shows in qualitative way the goodness of fit between simulation and full-scale measurements. Both algorithms give very similar best results, as expected according to their corresponding objective function value (see Fig. 1 (a)). This trend is confirmed for the other nine downburst events. The values of the 11 parameters which produces the best solution allows to reconstruct the geometrical and kinematical features of the downburst under consideration.

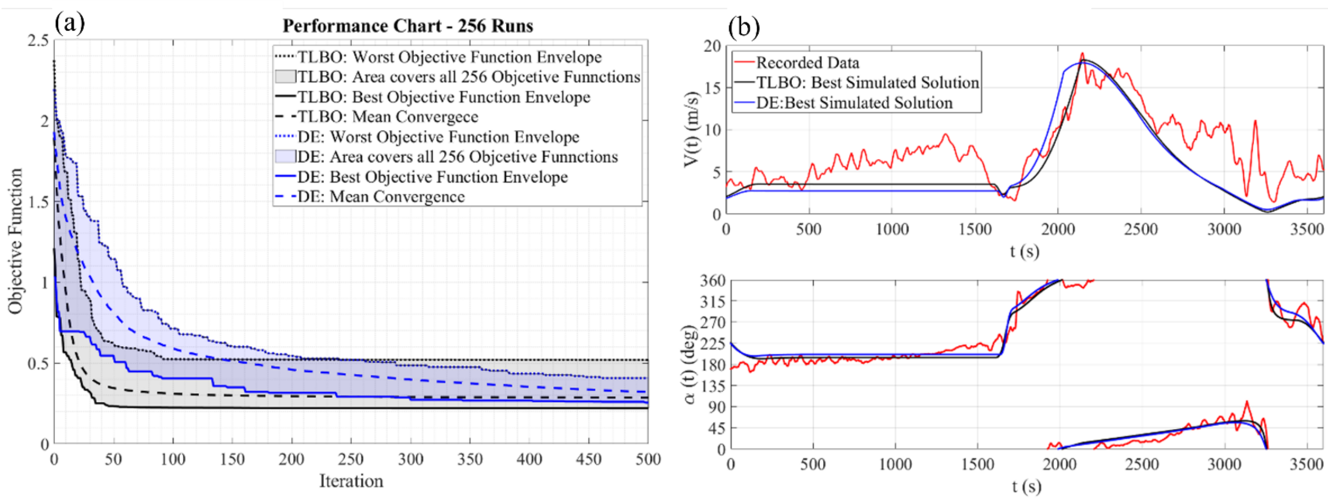

Figure 1. Performance chart (a) and simulations results (b) in terms of the moving average wind speed (top) and direction (bottom) for the downburst event occurred in Livorno on 4 October 2015.

Fig. 2 shows the reconstruction of the downburst wind field according to the best overall solution achieved with TLBO. The downburst outflow wind field is plotted at the height of the station/anemometer which in this case is equal to 20 m above the ground. The figure shows the downburst at its maximum intensity which is achieved 8.8 minutes after touch down. The downburst radius for this case is $R = 1500$ m, and the position at which maximum radial velocity is achieved is $R_{max} = 3550$ m. The downburst translation velocity is $V_t = 4.5$ m/s and the direction of translation is $\alpha_t = 300$ deg from the North (i.e., following the meteorological convention). The downburst reaches its maximum intensity at $T_{max} = 8.8$ minutes (see Fig. 2) and the whole phenomena last $T_{end} = 30$ minutes.

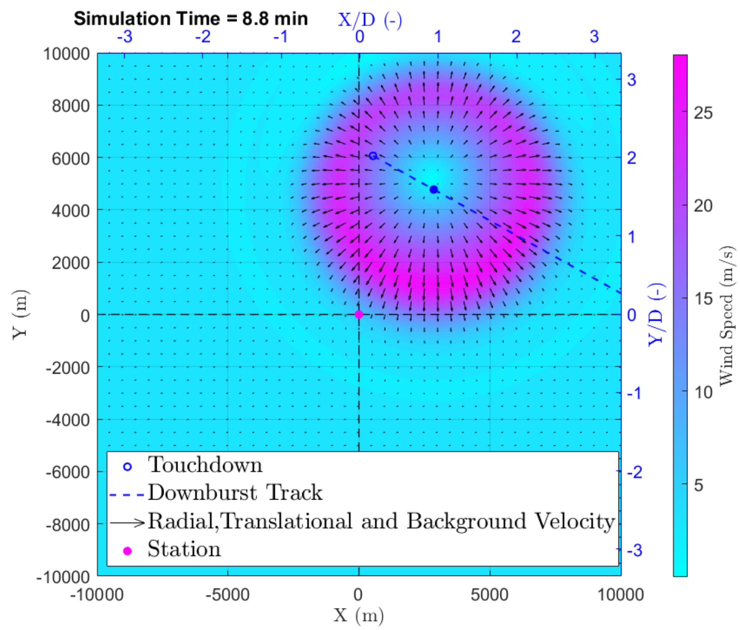

Figure 2. Wind field simulation of the downburst event occurred in Livorno on 4 October 2015. The bidimensional wind field is evaluated at the height of 20 meters above the ground. The simulation time referees at the instant of downburst maximum intensity. The letter D in the auxiliary axis referees to the downdraft diameter.

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