Chapter 18
Evolutionary Lagrangian Inverse Modeling for PM_{10} Pollutant Dispersion

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ABSTRACT

One of the main concerns when it comes to mitigating the effects of the concentration of the particulate matter PM_x in an area of study is the fact to determine its behavior over time, overcoming both physical and mathematical limitations in terms of a phenomenon of dispersion. Therefore, this chapter develops and analyzes a model based on the principles of evolutionary computation (EC) in order to determine the space-time behavior of the concentration of the particulate matter PM_x in a study area. The proposed model has three submodels within an integrated solution, which constitute the individual to evolve. The transformation of the possible solutions or generational population is made by using an asynchronous evolutionary model, due to genetic dependency between substructures. The proposed model was validated for configurations of n sources of emissions and m monitoring stations that measure the quality of the air in a study area.

INTRODUCTION

One of the main concerns when it comes to reducing the concentration values for particulate matter PM_x in a study area, is the fact to determine their spatial behavior over time. In order to describe this behavior, it is necessary to overcome a series of physical and mathematical constraints. From the physical point of view, the restrictions are determined by the number of monitoring stations for air quality that are located in an area of study, or by the inability to carry out campaigns that enable the identification of the behavior of a pollutant over time, especially in areas where access is difficult. From a mathemati-

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cal point of view, these constraints range from the spatial representation of the concentration over time, through the estimation of emissions at the source, the type of contaminant, and the discharge of pollutants from one of the *n sources* that can affect a particular point of a study area (Aceña et al., 2007), (Martin et al., 2007). So if we try to estimate emissions from sources there is only information available with respect to the concentration values measured in selected monitoring stations, but they do not deliver any information about the dispersion of pollutants within a study area. To solve this problem, geostatistics and computational intelligence have developed different methods of representation and interpolation, which in many cases do not fit the model of a specific phenomenon, mainly due to the size and the quality of the initial sample points representing the phenomenon in a study area (Cruzado, 2004). In the case of atmospheric phenomena, the set of points of the concentration for PM_x may suffer dynamic changes over time that depend on the sources of emission, the monitoring stations and their location, or on how they are linked up due to the dispersion phenomena. So in many cases methods are required to conduct search and adaptation, or that have memory so that a number of surfaces can be generated that, in terms of the phenomenon, adapt over time, and that enable decision making regarding the mitigation of the impact of this pollutant (Peña et al., 2009(a); Peña et al., 2009(b)).

That is why this chapter analyzes and develops a model based on the principles of evolutionary computation (EC), which includes two submodels in one solution or an individual to evolve, which is based on a *Kohonen Map Features Mode*l (KFM) (Galvan & Isazi,2004). The first substructure is used for estimating emissions in *n sources* from a series of measurements of the concentration for PM_x taken from *m* monitoring *stations* that they measurement the air quality. This substructure is associated with the *pattern of emissions* or input to the *KFM* model. The dynamics of the dispersion model, which is used for estimation, is governed by a *lagrangian gaussian puff tracking model* LGPT (Martín et al.,2002), which is based on the principles of a *backward gaussian puff tracking* (BGPT) (Israelsson et al.,2006). The second substructure permits to determine the spatial distribution of the concentration for PM_x, starting from identifying the concentration of *puffs* in the study area, thus *macropuffs* are generating a special type of functions, called *Non Uniform Puffs Functions* (NUPFS) (Peña & Hernandez,2007(a); Peña & Hernández,2007(b)). The model for the interpolation representation that determines the second structure is defined by the principles of a *Takagi– Sugeno Model* (TKS) (Sanchez et al., 2005) with *NUPFS* base functions. For the transformation of the possible solutions, or population of the present generation, the model uses an *asynchronous evolutionary model* (AEM), due to the genetic dependency between substructures. Finally, the proposed evolutionary model was validated in a real part of the study area, in which *n selected sources* of an industrial type and *m-monitoring stations* are located spatially. In order to validate this model, a study area, comprising an area of about 25*25 km^2, was selected in the Aburrá Valley, located in Antioquia, Colombia, South America.

BACKGROUND

The pollutant dispersion models have been used over time to determine the concentrations and flow and trace of elements according to the spatial distribution of sources and drains, the effect of the transport by flows mean and turbulent in the atmosphere, which are obtained from meteorological models or by detailed observation of the environment (Gallardo,1997). According to this dynamics, currently there are a number of questions that are directly related to how and in which form emissions of pollutants from different sources occur, or what is the contribution or

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