

# MODELING OF PM10 EMISSION WITH GENETIC PROGRAMMING

## MODELIRANJE EMISIJE PM10 Z GENETSKIM PROGRAMIRANJEM

Miha Kovačič<sup>1</sup>, Sandra Senčič<sup>2</sup>

<sup>1</sup>ŠTORE STEEL, d. o. o., Železarska cesta 3, 3220 Štore, Slovenia

<sup>2</sup>KOVA, d. o. o., Teharska cesta 4, 3000 Celje, Slovenia  
miha.kovacic@store-steel.si

*Prejem rokopisa – received: 2012-01-18; sprejem za objavo – accepted for publication: 2012-04-05*

To implement sound air-quality policies, regulatory agencies require tools to evaluate the outcomes and costs associated with various emission-reduction strategies. However, the applicability of such tools can also remain uncertain. It is furthermore known that source-receptor models cannot be implemented through deterministic modeling. The article presents an attempt of PM10 emission modeling carried close to a steel production area with the genetic programming method. The daily PM10 concentrations, daily rolling mill and steel plant production, meteorological data (wind speed and direction – hourly average, air temperature – hourly average and rainfall – daily average), weekday and month number were used for modeling during a monitoring campaign of almost half a year (23. 6. 2010 to 12. 12. 2010). The genetic programming modeling results show good agreement with measured daily PM10 concentrations. In future we will carry out genetic programming based dispersion modeling according to the calculated wind field, air temperature, humidity and rainfall in a 3D Cartesian coordinate system. The prospects for arriving at a robust and faster alternative to the well-known Lagrangian and Gaussian dispersion models are optimistic.

Keywords: steel plant, PM10 concentrations, modeling, genetic programming

V okviru uveljavljanja uredb o kvaliteti zraka, s ciljem zmanjševanja emisij, nadzorne agencije zahtevajo ovrednotenje emisij in stroškov, povezanih z njimi. Uporabnost takih orodij je v splošnem negotova. Prav tako je znano, da pri modelih tipa vir-sprejemnik težko uporabimo deterministično modeliranje. V članku je predstavljen poskus modeliranja emisije delcev PM10 na področju železarne z metodo genetskega programiranja. Osnova za modeliranje so bili podatki, zbrani v obdobju več kot pol leta (od 23. 6. 2010 do 12. 12. 2010): dnevne koncentracije PM10, produktivnost jeklarne, valjarne, meteorološki podatki (hitrost in smer vetra, temperatura zraka – urno povprečje ter padavine – dnevno povprečje) ter dan v tednu in zaporedna številka meseca. Rezultati modeliranja dnevnih koncentracij PM10 z genetskim programiranjem kažejo na dobro ujemanje z eksperimentalnimi podatki. V prihodnosti bomo izvedli modeliranje z genetskim programiranjem v kartezijskem 3D koordinatnem sistemu z upoštevanjem izračunanega vetrovnega polja, temperature zraka, vlažnosti in padavin. Možnosti za uporabo robustnih in hitrejših alternativ Lagrangovih in Gaussovih disperzijskih modelov so optimistične.

Ključne besede: železarna, koncentracije PM10, modeliranje, genetsko programiranje

## 1 INTRODUCTION

Particulate matter (PM) pollution is, especially in residential areas near industrial areas, a problem of great concern. This is not only because of the adverse health effects but also because of reduced visibility; on a global scale, effects on the radiative balance are also of great importance<sup>1-3</sup>.

To reduce PM levels in the air a deep knowledge of the contributing sources, background emissions, the influence of the meteorological conditions, as well as of PM10 formation and transport processes is needed.

However, current state-of-the-art PM10 modeling does not allow us to quantitatively model the whole range of emissions behavior, which is why the dispersion modeling is thus increasingly connected with intelligent algorithms such as artificial neural networks<sup>4-9</sup> and evolutionary computation<sup>9</sup>.

The objective of this work was to model PM10 emissions close to a steel plant area in Slovenia by means of a genetic programming method. Genetic programming has been proven to be an effective optimi-

zation tool for multicriterial and multiparametrical problems<sup>10-13</sup>. The genetic programming system for PM10 emission modeling imitates the natural evolution of living organisms, where in the struggle for natural resources the successful entities gradually become more and more dominant in adapting to the environment in which they live; the less successful ones, meanwhile, are only rarely present in subsequent generations. In the proposed concept the mathematical models for PM10 concentration prediction undergo adaptation. During the simulated evolution more and more successful organisms (PM10 emission models) emerge on the basis of given data (wind speed and direction – hourly average, air temperature – hourly average, rainfall – daily average, weekday and month number).

In order to allow for a self-contained paper the basic terms and experimental setup are stated in the beginning. Afterwards the idea of the proposed concept is presented. In the conclusion the main contributions of the performed research are summarized, while guidelines for further research are provided.

## 2 EXPERIMENTAL SETUP

### 2.1 Sampling sites

Figure 1 shows the locations of the sampling sites, rolling mill, steel plant and residential areas. Due to rolling mill and steel plant PM10 contribution also several source categories influence the PM10 concentrations. These include combustion and non-combustion traffic sources, urban background concentrations, along with both contributions that are transported by regionally and long-range.

### 2.2 Sampling

Samples for this study were collected between 23. 6. 2010 and 12. 12. 2010. Sampling was performed 1.5 m above the ground. PM10 samples were collected for 24 h on Mondays using low-volume samplers equipped with EPA-equivalent size-selective inlets. Particles with diameter 10 µm (PM10) were collected on cellulose esters membranes with high collection efficiencies (99 %). In total 172 PM10 samples for each sampling site were available.

Before and after the samplings were made the filters were exposed for 24–48 h on open but dust-protected sieve-trays in an air-conditioned weighing room. The gravimetric determination of the mass was carried out using an analytical microbalance (precision 1 µg) located in the weighing room. In order to remove static electricity from filters the balance is equipped with a special kit in a Faraday shield.

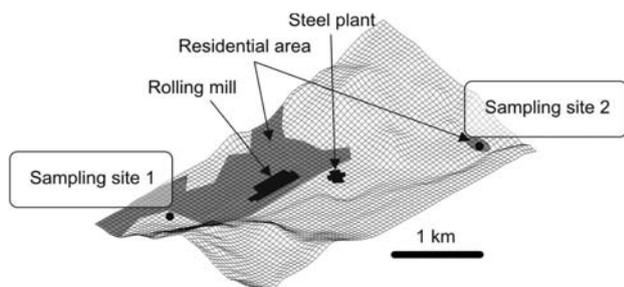


Figure 1: Topographic view of the study area

Slika 1: Topografski prikaz področja študije

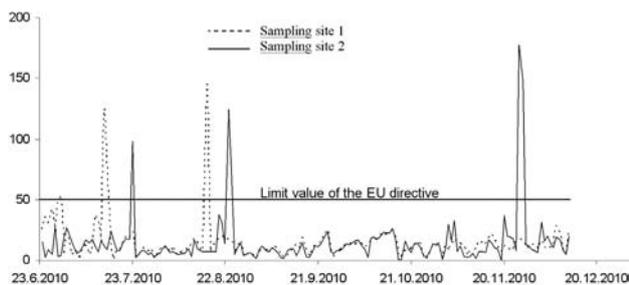


Figure 2: The measured PM10 concentrations during the study period for the sampling sites

Slika 2: Izmerjene koncentracije PM10 v obdobju študije za lokaciji vzorčenja

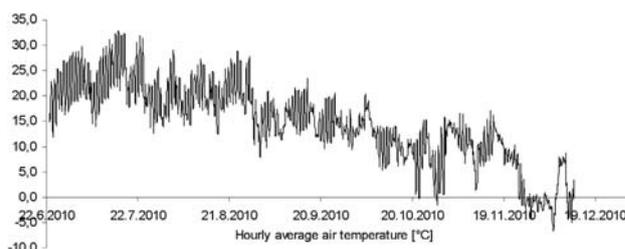


Figure 3: The hourly average temperatures during the study period

Slika 3: Urno povprečje temperature zraka v obdobju študije

The limit value of the EU directive – i.e. a daily mean PM10 concentration – is 50 µg/m<sup>3</sup>. At the sampling site 1 and 2 the measured PM10 concentration exceeded limit value four times and five times, respectively.

Figure 2 shows the measured PM10 concentrations during the study period for the sampling sites.

### 2.3 Meteorological data

Hourly average air temperature, wind speed and direction and daily rainfall data were made available to the authors by the Slovenian Environment Agency.

Figure 3 shows the hourly average temperatures during the study period.

Figure 4 shows the frequency distribution of wind direction and wind speed obtained based on wind direction and speed data measured every hour during the study period.

Figure 5 shows the daily rainfall during the period of the study.

The hourly data based on electric arc and rolling mill production was collected during the study period. During

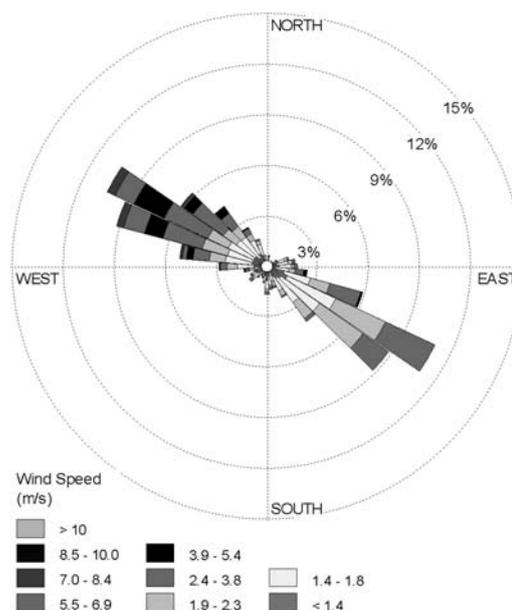


Figure 4: Frequency distribution of wind direction and wind speed

Slika 4: Frekvenčna porazdelitev smeri in hitrosti vetra

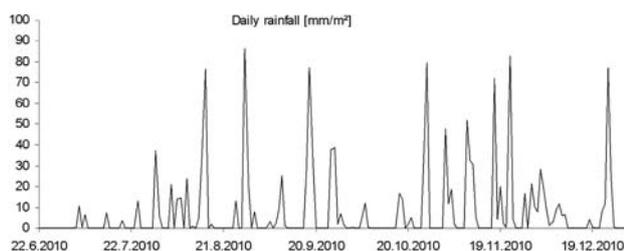


Figure 5: Daily rainfall during the study period  
Slika 5: Dnevne padavine v obdobju študije

the study period, the electric arc furnace was stopped for 28 465 min and the rolling mill was stopped for 8 213 min. Figure 6 shows the minutes of stopping per day for the electric arc furnace and rolling mill during the study period.

### 3 GENETIC PROGRAMMING MODELING

Genetic programming is probably the most general evolutionary optimization method. The organisms that undergo adaptation are in fact mathematical expressions (models) for the PM10 concentrations prediction in the present work. The concentration prediction is based on the available function genes (i.e., basic arithmetical functions) and terminal genes (i.e., independent input parameters, and random floating-point constants). In the present case the models consist of the following function genes: addition (+), subtraction (-), multiplication (\*) and division (/), and the following terminal genes: weekday (WEEKDAY) and month number (MONTH), wind speed [m/s] (SPEED), wind direction [°] (DIRECTION), air temperature [°C] (TEMP), rainfall [mL] (RAIN), electro arc furnace efficiency [min/h] (EAF), rolling mill efficiency [min/h] (ROLLING). In order to ascertain the influence of seasons and traffic during workday hours the weekday and month number were also added as terminal genes. One of the randomly generated mathematical models – # – is schematically represented in Figure 7 as a program tree with included function genes (\*, +, /) and terminal genes (TEMP, RAIN, EAF and a real number constants 2 and 5.1).

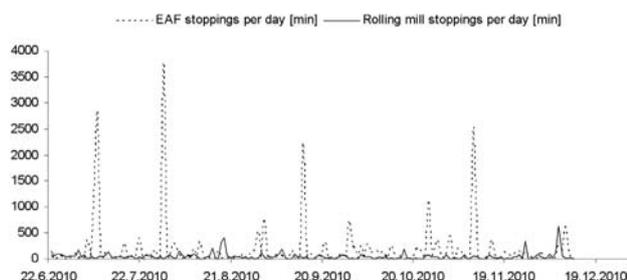


Figure 6: Minutes of stopping per day for the electric arc furnace and rolling mill during the study period  
Slika 6: Dnevni zastoji elektrobločne peči in valjarne v minutah v obdobju študije

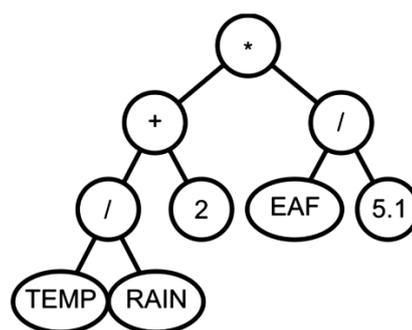


Figure 7: Randomly generated mathematical model for the PM10 concentrations prediction, represented in program tree form.

Slika 7: Naključno ustvarjen matematični model napovedovanja koncentracije PM10, predstavljen kot programsko drevo

Random computer programs of various forms and lengths are generated by means of the selected genes at the beginning of the simulated evolution. The varying of the computer programs is performed by means of the genetic operations during several iterations, known as generations. After the completion of the variation of the computer programs a new generation is obtained. Each generation is compared with the experimental data. The process of changing and evaluating organisms is repeated until the termination criterion of the process is fulfilled. The maximum number of generations is chosen as a termination criterion in the present algorithm.

The following evolutionary parameters were selected for the process of simulated evolutions: 500 for the size of the population of organisms, 100 for the maximum number of generations, 0.4 for the reproduction probability, 0.6 for the crossover probability, 6 for the maximum permissible depth in the creation of the population, 10 for the maximum permissible depth after the operation of crossover of two organisms, and 2 for the smallest permissible depth of organisms in generating new organisms. Genetic operations of reproduction and crossover were used. For selection of organisms the tournament method with tournament size 7 was used<sup>9-13</sup>. 100 independent civilizations of mathematical models for prediction of the PM10 concentration were developed. The best evolution sequence of 100 generations was computed in 8 h and 41 min on 2.39 GHz processor and 2 GB of RAM by an AutoLISP based in-house coded computer program.

The model fitness  $f$  has been defined as:

$$f = \sum_{i=1}^n (P_i - M_i) + N \cdot 10000 \quad (1)$$

where  $n$  is the size of sample data and,  $P_i$  is predicted PM10 concentration,  $M_i$  is measured PM10 concentration and  $N$  is the number of all cases when:

$$P_i < 50 \wedge M_i > 50 \vee M_i < 50 \wedge P_i > 50 \quad (2)$$

The limit value of the EU directive, i.e. a daily mean PM10 concentration, is  $50 \mu\text{g}/\text{m}^3$ . The number  $N$  tells us when the prediction is above that limit value, when in

order to assure PM10 concentration exceedance prediction by developed predictive model it should in fact be below the limit, and also when prediction by developed predictive model should be above the limit.

The simulated evolution in one run of the genetic programming system (out of 100) produced the following best model for prediction of PM10 concentration for sampling site 1:

$$\left( \text{DIRECTION} + \left( \text{DIRECTION} + \text{MONTH} + \text{WEEKDAY} + \frac{\text{SPEED}(-1.99563 + 3 \text{ WEEKDAY} + 4 \text{ MONTH WEEKDAY})}{\text{MONTH} - \text{WEEKDAY}} \right) + \frac{\text{WEEKDAY}(-1.99563 + \text{MONTH WEEKDAY})}{\text{MONTH} - \frac{1}{2} \text{ MONTH WEEKDAY}} \right) \left( \frac{-1.99563 + \text{MONTH WEEKDAY}}{\text{MONTH} + \text{WEEKDAY} - \frac{1.99563 + \text{MONTH WEEKDAY}}{\text{MONTH WEEKDAY}}} \right) + \left( (-1.99563 + \text{MONTH WEEKDAY}) \left( -\text{MONTH} + (\text{DIRECTION} - \text{WEEKDAY}) \right) \left( \text{DIRECTION} + \text{WEEKDAY} + \text{MONTH WEEKDAY} - \frac{\text{MONTH SPEED}(-1.99563 + \text{MONTH WEEKDAY})}{-\text{DIRECTION} + \text{MONTH} + \text{WEEKDAY}} \right) \right) \left( \frac{\text{MONTH}^2(-1.99563 + \text{MONTH WEEKDAY})}{\text{MONTH} - \frac{\text{WEEKDAY}}{\text{DIRECTION}}} \right) \left( \frac{\text{MONTH} - \frac{2 \text{ WEEKDAY} + \text{MONTH WEEKDAY}}{\text{DIRECTION WEEKDAY}}}{\text{DIRECTION} - \text{RAIN} + \left( \text{MONTH} - \frac{\text{MONTH} - \text{WEEKDAY}}{\text{WEEKDAY}} \right) + \text{MONTH WEEKDAY} - \left( -\text{MONTH} + \left( \text{MONTH} - \frac{\text{MONTH} - \text{WEEKDAY}}{\text{SPEED}} \right) \right) (-1.99563 + \text{MONTH WEEKDAY})} \right) \right) \right) \right) \quad (3)$$

with fitness of 1019.95, number  $N = 0$  and average deviation of  $5.96 \mu\text{g}/\text{m}^3$ .

The best evolutionary developed model (out of 100) for prediction of PM10 concentration for sampling site 1 is:

$$\left( -5.76596 + \text{MONTH} + \frac{\text{TEMP}}{\text{DIRECTION}} \right) \left( \frac{\text{SPEED} - \frac{\text{SPEED}}{\text{TEMP}}}{\text{MONTH}} + \frac{\left( \frac{\text{MONTH} - \text{TEMP}}{\text{DIRECTION} - \text{WEEKDAY}} \right) \text{WEEKDAY}}{\text{EAF} + \frac{\text{SPEED} - \text{TEMP}}{\text{DIRECTION} - \text{TEMP}}} \right) \left( \frac{\text{TEMP} + \frac{\text{SPEED}}{\text{TEMP}}}{\text{TEMP} + \frac{\text{SPEED}}{\text{TEMP}} + \frac{\text{EAF RAIN SPEED}}{\text{TEMP} + \text{WEEKDAY}}} \right) \left( \frac{\text{DIRECTION WEEKDAY}}{\text{DIRECTION WEEKDAY}} \right) + \frac{\text{MONTH} - \frac{\text{WEEKDAY}^2}{\text{TEMP}} + \frac{\text{SPEED TEMP}^2}{\text{WEEKDAY} (\text{DIRECTION} + \frac{\text{TEMP} - \text{TEMP WEEKDAY}}{\text{DIRECTION}})}}{\text{DIRECTION} + \frac{\text{MONTH} - \text{WEEKDAY} + \frac{\text{EAF WEEKDAY} - \text{TEMP WEEKDAY}}{\text{SPEED TEMP} - \text{DIRECTION}}}{\text{EAF} + \frac{\text{EAF RAIN} - \text{TEMP WEEKDAY} - \text{TEMP WEEKDAY}}{\text{DIRECTION}}}} + 0.30872 \quad (4)$$

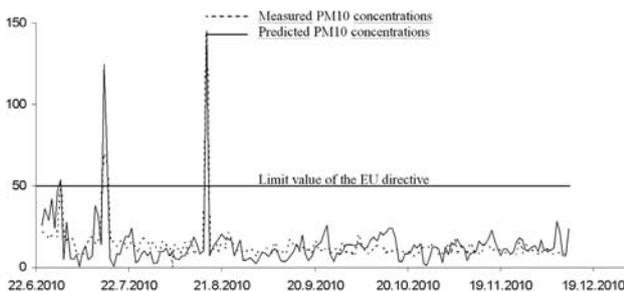


Figure 8: Measured and predicted PM10 concentrations [ $\mu\text{g}/\text{m}^3$ ] for sampling site 1

Slika 8: Izmerjene in napovedane koncentracije PM10 [ $\mu\text{g}/\text{m}^3$ ] za lokacijo vzorčenja 1

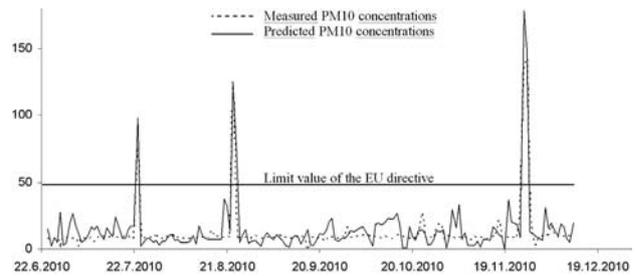


Figure 9: Measured and predicted PM10 concentrations [ $\mu\text{g}/\text{m}^3$ ] for sampling site 2

Slika 9: Izmerjene in napovedane koncentracije PM10 [ $\mu\text{g}/\text{m}^3$ ] za lokacijo vzorčenja 2

with fitness of 11 124.67, number  $N = 1$  (on the 30. 6. 2010 the measured PM10 concentrations were  $53.6 \mu\text{g}/\text{m}^3$  and predicted  $21.41 \mu\text{g}/\text{m}^3$ ), and average deviation of  $6.54 \mu\text{g}/\text{m}^3$ .

Figures 8 and 9 show measured and predicted PM10 concentrations for sampling sites 1 and 2, respectively.

#### 4 CONCLUSIONS

This paper presented the possibility of the PM10 concentration prediction close to a steel plant area with genetic programming. The daily PM10 concentrations, daily rolling mill and steel plant production, meteorological data (wind speed and direction – hourly average, air temperature – hourly average and rainfall – daily average), weekday and month number were used for modeling during a monitoring campaign of almost half a year (23. 6. 2010 to 12. 12. 2010). The special fitness function for genetic programming system was designed in order to assure also PM10 limit value exceedance prediction. For each sampling site the best models for PM10 prediction were obtained from 100 runs of the genetic programming system. The model for sampling sites 1 and 2 predicts concentrations within an average error range of  $5.96 \mu\text{g}/\text{m}^3$  and  $6.54 \mu\text{g}/\text{m}^3$ , respectively. All exceedances of the EU directive limit value ( $50 \mu\text{g}/\text{m}^3$ ) were administered at sampling site 1, but only 4 out of 5 of these occurred at sampling site 2. In the future we will carry out genetic programming based dispersion modeling according to the calculated wind field, air temperature, humidity and rainfall in a 3D Cartesian coordinate system. The prospects for arriving at a robust and faster alternative to the well-known Lagrangian and Gaussian dispersion models are optimistic.

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