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NO_2 Dispersion Model of Emissions of a 20 kWe Biomass Gasifier

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Biomass valorization represents a simple way to reduce Green House Gases emissions. However, the biomass-to-energy field is limited by high gaseous emission concentrations. Innovative abatement technologies can make gaseous emissions close to zero. In this work, three different NO_2 abatement technologies were assessed and compared. A deterministic approach was used to estimate NO_2 concentrations using experimental concentrations at the chimney for a 20 kWe biomass gasifier. The gasifier chimney was described as an equivalent stack. The pollutant propagation was simulated with a Gaussian plume dispersion model. On this purpose, the unknown equivalent stack flow rate in the model was adjusted using the available data of NO_2 on the ground, considering the changing of the air stability between nighttime and daytime and the variable wind direction. Thanks to pollutants dispersion modeling, the evaluation of the optimal abatement technology was possible, investigating the potential effect produced on people and the environment. Results show a bioscrubber technology as the best one to reduce NO_2 concentrations at 100, 1000, 3000 m from the emission point of 74, 75, 70 %, respectively.

1. Introduction

Cogeneration or Combined Heat and Power (CHP) definition is the simultaneous generation of two different forms of useful energy by one primary energy source. Cogeneration can be a solution for energy saving and environmental preservation, due to the application of a heat exchangers kit to absorb and recover exhaust heat (Sofia et al., 2020c). In this sense, cogeneration plants can achieve energy efficiency levels around 90% and could reduce greenhouse gas emissions by up to 250 million tonnes by 2020 (Sofia et al., 2020a). Many research studies have been conducted in recent years to improve the economic and environmental efficiency and effectiveness of biomass cogeneration systems (Sofia et al., 2013). However, the biomass-to-energy field is limited by the high gaseous emissions that can emit (Sonarkar and Chaurasia, 2019). In particular, PM (10 and 2.5), CO and NOx are considered having concentrations higher than small power plants fed by fossil sources (e.g., natural gas) (Petrov et al., 2017). Due to these reasons, biomass power plant emissions often represent a limit to the diffusion of these plants due to the lack of social acceptance (Giuliano et al., 2018b). Dispersion modeling was carried out for the estimation of NO_2 concentrations from biomass power plants by Chusai et al. (2012), whereby biomass burning was the most influence (>90%) on the air quality respect fossil-based sources. Petrov et al. (2017) studied the NO_2 emissions from the small-scale biomass gasification plant with no engineered pollution controls, concluding that advanced high-efficiency pollution control devices are essential to lower emissions for emission sources located in a densely populated community. Biomass Combined heat and power systems are operated with solid fuels, such as residual lignocellulose material, grasses or fruits as well as more or less every other organic residue. The lignocellulosic biorefineries' waste solid material is valorized by cogeneration systems, as combustion or gasification of lignin-rich streams (Giuliano et al, 2018a). From gasification, the raw syngas is obtained and conditioned in order to feed an engine (La Villetta et al., 2017). Generally, small CHP plants (until 1 MWe) are used for domestic, local heating and residential buildings, while medium and large CHP plants (more than 2 MWe) are used for larger buildings, industrial sites or district heating grids. Biomass gasification plants with a size less than 200 kWe can have a high diffusion if they guarantee air pollution levels less than traditional fossil-based equivalent plants. Thus, pollution monitoring technologies must be applied to model their spread (Sofia et al., 2018). Correct positioning of monitoring points for concentrations of pollutants allows the identification of the source of polluting emissions (Sofia et al., 2019). The mitigation of pollution also passes through the utilization of innovative and bio-based processes to produce thermal energy and electricity (Sofia et al., 2020b). In this work, a deterministic approach was used to estimate NO_2 concentrations using experimental concentrations at the chimney for a 20 kWe biomass gasifier. The gasifier chimney was described as an equivalent stack. The pollutant propagation was simulated with a Gaussian plume dispersion model. On this purpose, the unknown equivalent stack flow rate in the model was adjusted using the available data of NO_2 on the ground considering the changing of the air stability between nighttime and daytime and the variable wind direction. Thanks to pollutants dispersion modeling, the evaluation of the optimal abatement technology was possible, investigating the potential effect produced on people and the environment.

1.1 Gaussian plume

The NO_2 dispersion after the gasification process has been described using a Gaussian Plume dispersion model. The concentration of gas aerosols at a certain point of coordinates x, y, z, from a continuous source with an emission height, H can be described by the following equation (Turner, 1970):

$$C(x,y,z;H) = \frac{Q}{2\pi\sigma_y\sigma_z u} exp\left[-\frac{1}{2}\left(\frac{y}{\sigma_y}\right)^2\right]\left\{exp\left[-\frac{1}{2}\left(\frac{z-H}{\sigma_z}\right)^2\right] + exp\left[-\frac{1}{2}\left(\frac{z+H}{\sigma_z}\right)^2\right]\right\} \quad (1)$$

Where Q is the uniform pollutant emission rate, g/s, u is the mean wind speed affecting the plume, m/s, σ_y is the plume distribution standard deviation in the horizontal direction, m, σ_z is the plume distribution standard deviation in the vertical direction, m, H is the effective emission height, m.

Equation 1 is obtained assuming that the plume spread as a Gaussian distribution along the horizontal and vertical planes, and there is no deposition or reaction at the ground surface.

The values of are σ_y and σ_z vary with the characteristics of the atmosphere, height above the surface, surface roughness, sampling time to evaluate the concentrations, wind speed, and the downwind distance from the source, *x*.

Considering that the concentration of practical interest is that of fallout at ground level ($z = 0$) and on the centreline of the plume ($y = 0$), the concentration of pollutant, on the ground, *C(x,0,0)*, in the geometric coordinates of point *P(x, 0,0)*, downwind, considering all reflections of the plume is negligible, the Equation 1 reduces to:

$$C(x,0,0;H) = \frac{Q}{\pi\sigma_y\sigma_z u}\left[-\frac{1}{2}\left(\frac{H}{\sigma_z}\right)^2\right] \quad (2)$$

Most of the experimental activities promoted in the study of the dispersion of pollutants in the planet boundary layer (PBL) were aimed at obtaining useful data for the formulation of semi-empirical relationships to describe the two standard deviations of the dispersion as a function of the Stability Classes Atmospheric and downwind distance. This dependence implies that the semi-empirical relationships inferred are strictly related to the scheme used in the experimental surveys to define the Stability Classes. So, when employing a Gaussian Plume model, congruence between the definition of the Stability Class and the semi-empirical relationships used should be guaranteed. There have been many relationships proposed by various researchers, but only two are actually used in current modeling practice. However, it should be remembered that these correlations can be considered valid for leeward distances between 100 meters and 10 - 20 km.

Among the relationship to calculate σ_y and σ_z, the most used are the Pasquill-Gifford correlations (Hossain, 2014). The Pasquill-Gifford correlations were integrated by Turner (Turner, 1970), who obtained graphical elaborations that related the two standard deviations, σ_y and σ_z, to the downwind distance as a function of atmospheric stability classes (obtained through the schemes proposed by Pasquill-Turner). From these graphic representations, the analytical relationships were deduced. The analytical relationship most used in practice and for this study is proposed by Green et al. (Green et al., 1980), expressed as follows (Equation 3, 4):

$$\sigma_y(x) = \frac{k_1 x}{\left[1+\left(\frac{x}{k_2}\right)\right]^{k_3}} \quad (3)$$

$$\sigma_z(x) = \frac{k_4 x}{\left[1 + \left(\frac{x}{k_2}\right)\right]^{k_5}} \tag{4}$$

The constants values (k_1, k_2, k_3, k_4, and k_5) are reported in Table 1. Figure 1 presents the trend with the downwind distance of the horizontal and vertical standard deviation depending on the Atmospheric Stability Class.

Table 1: Constants of Green correlations

Stability class	k_1	k_2	k_3	k_4	k_5
A	0.2500	927	0.189	0.1020	-1.918
B	0.2020	370	0.162	0.0962	-0.101
C	0.1340	283	0.134	0.0722	0.102
D	0.0787	707	0.135	0.0475	0.465
E	0.0566	1070	0.137	0.0335	0.624

Atmospheric stability

The concepts of stability, neutrality, and atmospheric instability are related to the physical conditions of the air mass dynamic balance. Atmospheric instability is a meteorological condition that favors the air particles' vertical movements and, therefore, the polluting substances mixing, dispersion, and dilution. Conversely, a condition of atmospheric stability hinders these vertical motions, prevents mixing and dispersion, and favors the pollutant accumulation. An intermediate condition to the previous ones, therefore, represents a condition of neutrality. Conventionally, stability can be classified as A - highly unstable and B - unstable; C - slightly unstable and D - neutral; E - slightly stable and F - stable. The stability classes, according to Hossain (Hossain, 2014), are calculated based on wind speed, daytime solar radiation, and nighttime cloudiness.

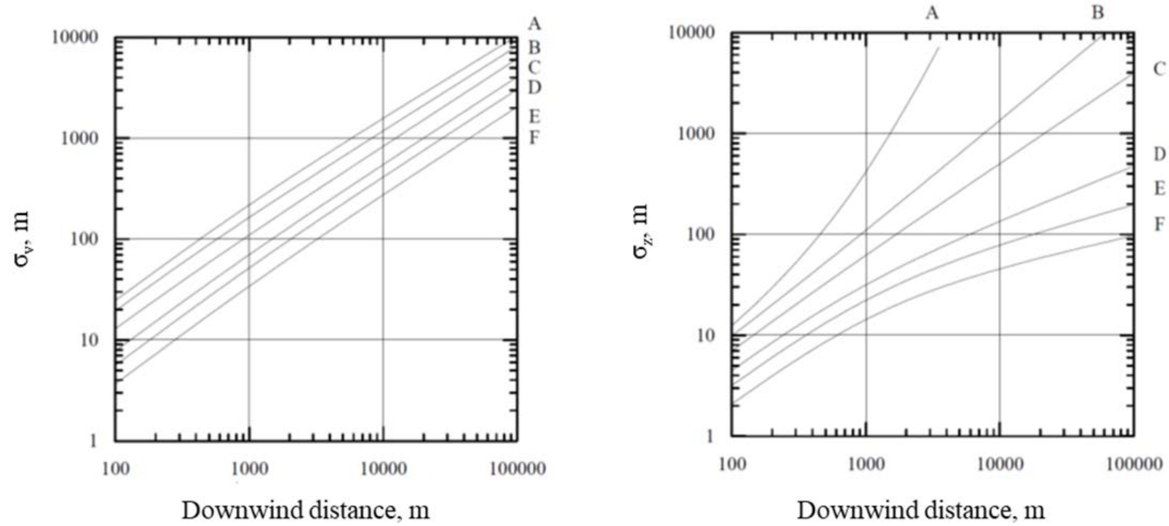

Figure 1: Gaussian Plume standard deviations value according to Pasquill-Gilfford

1.2 Data implemented

The Gaussian Plume dispersion model was calculated using a Matlab code developed for the present study. The NO_2 mass flow rate Q_{out} was calculated according to the following equation:

$$Q_{out} = C_{out} V \tag{5}$$

Considering conditions at the gasifier outlet shown in Table 2. Where S is the gasifier section, Q_{in} is the inlet mass flow rate, t_f is the operating time and T_{out} is the outlet stream temperature. C_{out} represents the measured NO_2 outlet concentration.

Table 2: Conditions at the gasifier outlet

S (m^2)	*Q_{in} (t/y)*	*t_f (h/y)*	*T_{out} (°C)*	*H (m)*
0.09	300	7200	800	3

In this study, four different values of NO_2 concentrations corresponding to four separation methods were investigated. In detail, the NO_2 concentrations investigated were from the Eco20 gasifier, a Cyclone, a Washing Tower and, a Bioscrubber all considered at 20 kW (Table 3).

Table 3: NO_2 outlet concentrations

Operation	NO_2 outlet concentration, mg/m^3
ECO20 gasifier	297.15
Cyclone	289.6
Washing Tower	237.5
Bioscrubber	77.4

The residual NO_2 concentrations', evaluated at three different distances from the plant emission point, were calculated to investigate the effect of the Gaussian Plume dispersion. The distance investigated were 100 m, 1000 m, and 3000 m.

As described by Equation 1, the parameters to calculate the Gaussian Plume dispersion includes information about the wind field. Investigating the plant background, it was clear that the wind field characteristics is the prevailing one. This condition allows the wind comes from a prevailing wind direction that can fluctuate in a small range of degrees. The wind intensity and direction values were set as the average of the wind measured in the last year at the plant location (https://globalwindatlas.info/) and resulting from being equal to 5.5 m/s in the West-South-West direction. The stability class used in the case studied is the neutral class D. The neutral stability class is representative of the wind intensity value used and represents well both the diurnal and nocturnal conditions. The σ_y and σ_z values at the three distances considered were calculated considering the kn values in Table 1 for the D stability class.

2. Results

Figure 2 clearly shows the concentrations on the ground estimated by the Gaussian plume in conditions of atmospheric neutrality (class D). From the values shown in table 4 it can be seen how the Eco20 gasifier, the cyclone and the washing tower have similar trends. Starting from very similar values of NO_2 concentrations, after 3000 m reach similar values. The Gaussian plume model applied to the bioscrubber returns a trend proportional to that of the operations analyzed above, albeit with lower values. In particular, after 100 m there is a reduction in the NO_2 concentration ranging from 1.05% of the Eco20 gasifier to 1.10% of the bioscrubber; after 3000 m all the operations considered have decreased by 99.98% compared to the start. The maximum concentration is reached in all four cases at 50 m from the emission point. Concentrations decay occurs more rapidly with the bioscrubber reaching after about 1700 m concentrations values tending to zero, while for the other operations considered this reduction also extends beyond the 3000 m considered.

The determination of the ground concentrations due to the dispersion of NO_2 allows the identification of any critical areas in which to operate if necessary to reduce further the NO_2 concentrations exiting the operations considered. Therefore, the dispersion of the Gaussian plume depends not only on the atmospheric conditions but also on the initial concentration measured at the emission point. With the same atmospheric stability conditions, the lower the concentration at the emission point, the less space will be necessary for the complete dispersion of NO_2.

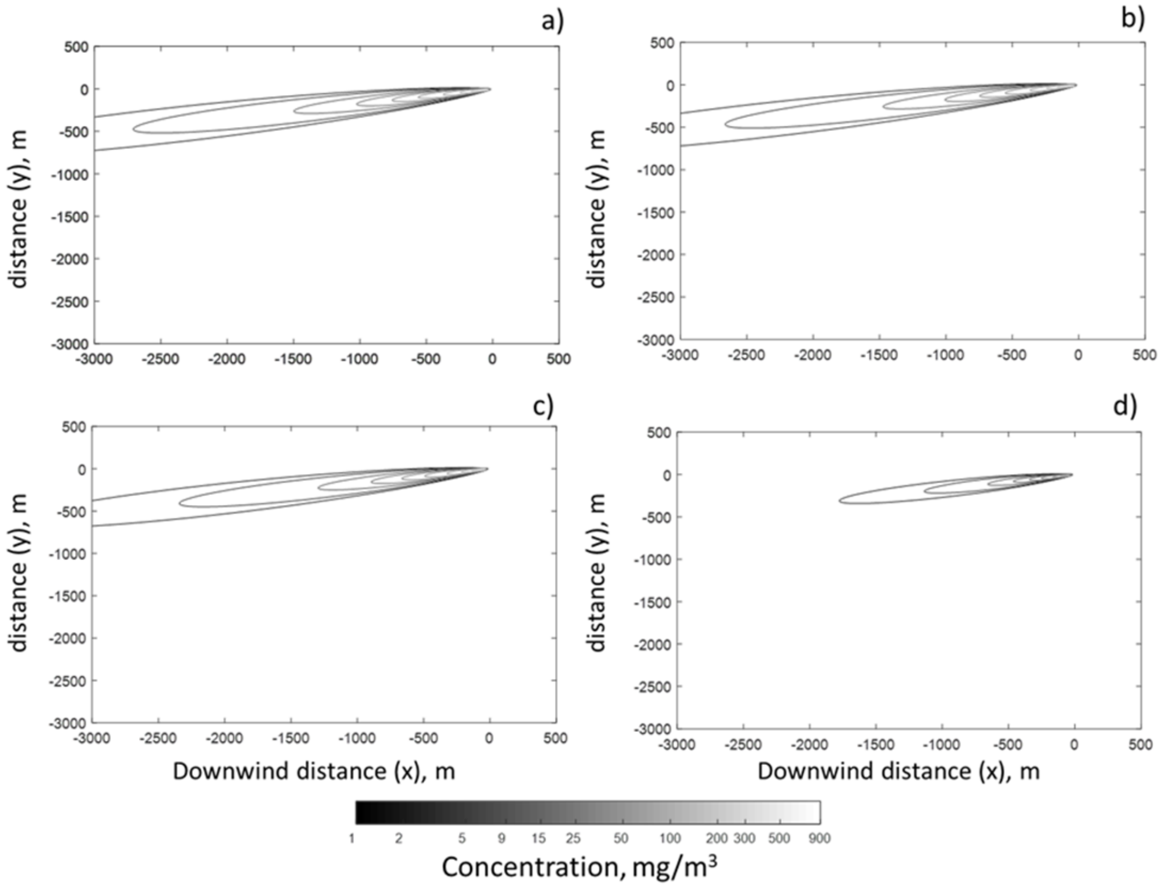

Figure 2: Gaussian Plume standard deviations value according to Pasquill-Gilfford

The concentration values estimated by the Gaussian plume model are strongly influenced by the atmosphere physical conditions. Atmospheric instability is a meteorological condition that favors the air particles vertical movements and, therefore, the mixing, dispersion and dilution of polluting substances. Conversely, a condition of atmospheric stability hinders these vertical motions, prevents mixing and dispersion and promotes the accumulation of pollutants. An intermediate condition to the previous ones therefore represents a condition of neutrality.

Table 4: NO_2 concentration results

Operation	NO_2 concentration, mg/m3, at			
	0 m	100 m	1000 m	3000 m
Eco20 Gasifier	297.14	294.01	0.51	0.03
Cyclone	289.62	286.43	0.5	0.03
Washing Tower	237.45	234.84	0.41	0.028
Bioscrubber	77.38	76.52	0.13	0.009

3. Conclusions

In this work, A deterministic approach was used to estimate NO_2 concentrations using experimental concentrations at the chimney for a 20 kWe biomass gasifier. Four different pollutant abatement systems were compared in terms of NO_2 concentration at four different distances from the chimney. In particular, without specific abatement system case, cyclone, washing tower a bioscrubber technologies were considered thanks to the availability of experimental data. The Gaussian Plume dispersion model was used to estimate NO_2 concentrations at 100, 1000 and 3000 m from the chimney. Atmospheric stability and meteorology were considered in the analysis using the stability classes. Model results show the quick diffusion of pollutants considering the difference of concentrations between distances 100 and 1000 m. In this 900 m of distance

NO_2 concentrations decrease of about 99.8 %. At 3000 m the concentrations are less than 0.01 mg/m3. Comparison between four different abatement technologies leads to the bioscrubber as the optimal technology. Results show a bioscrubber technology as the best one to reduce NO_2 concentrations at 100, 1000, 3000 m from the emission point of 74, 75, 70 % respectively. This abatement process, together with the small scale CHP systems, can be the next generation of residual solid biomass utilization strategies to valorize solid waste from agricultural activities in the rural areas.

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