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Evaluating the Impact of Computational Time Interval on Livestock Odour Dispersion Using a Computation Fluid Dynamics Model

Y. Li, Postdoctoral Fellow

Department of Agricultural and Bioresource Engineering; Institute of Agricultural Rural and Environmental Health, University of Saskatchewan. Saskatoon SK

H. Guo, Assistant Professor

Department of Agricultural and Bioresource Engineering, University of Saskatchewan. Saskatoon SK

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Abstract. A Computational Fluid Dynamics (CFD) model with Eulerian-Lagrangian approach was applied to predicted odour dispersion from a 3000-sow farrowing operation. Eulerian-Lagrangian approach solved turbulent air flow within Eulerian reference frame, and then calculated trajectories of discrete particles in continuous flow field within Lagrangian reference frame. Weather variables were taken every minute by the on-site weather station. The measured weather variables were synthesized into meteorological data with time intervals of 1, 10, 20, 30, and 60 min by Meteorological Processor for Regulatory Models (MPRM). Odour concentrations predicted by CFD model with different model computational time intervals were compared to evaluate the effects of time interval on odour dispersion. Predictions with 1 h time interval overestimated downwind odour concentration and travel distance compared with the predictions with sub-hour time intervals. The longer the time interval, the higher the odour concentration and the longer travel distance would be. Short time intervals (e.g. $\Delta t = 1$ min) used in the prediction were more sensitive to wind direction shift and provided more accurate instantaneous odour plumes than longer time intervals. However application short time interval required more refined meteorological data.

Keyword. Computational Fluid Dynamics, Odour, Swine, Air dispersion model, Time interval.

INTRODUCTION

Environmental and health concerns on odour emission from concentrated animal feeding operations (CAFOs) spurred many states and provinces in the US and Canada to address the odour issue in local regulations directly or indirectly using methods such as setbacks, permitting, and restrictions (Redwine et al., 2000). Both field measurements by human panellists and dispersion modeling have been employed to quantify odour emission and dispersion for the purpose of regulation. Field measurements are time-consuming and the measured results apply only to the weather conditions when the measurements are taken (Guo et al., 2005). Application of air dispersion models to predict downwind odour concentration became a more common practice due to their capability of accounting for the wide variations of meteorological and topographical conditions. Many air dispersion models, e.g. ISCST3, INPUFF-2, CALPUFF, AERMOD, and AUSPLUME etc. are based on Gaussian plume or puff model and have been used to simulate odour dispersion from livestock facilities (Smith, 1995; Zhu et al., 2000; Guo et al., 2001; Sheridan et al., 2004; Zhou et al., 2005). Zhu et al. (2000) and Guo et al. (2001) evaluated INPUFF-2 for short-distances (< 500 m) with odor field plume data collected by trained field assessors, and for long-distances with odor measurement data obtained by trained resident odor observers on rural area. Sheridan et al. (2004) used ISCST3 to assess odour impact from a 1000-sow integrated pig unit in Ireland.

Most of air dispersion models available now for odour predictions were originally developed for industrial sources and served as regulatory tools for industrial pollutants, e.g. ISCST3, designed to support the Environment Protection Agency of the United States (US EPA) regulatory modeling programs; AUSPLUME, developed to serve as a regulatory dispersion model in Australia by Australian Environmental Protection Authority (AEPA); INPUFF-2, originally developed by the US EPA, and marketed commercially by Bee-Line Software Co., Asheville, NC; CALPUFF, recommended by US EPA for characterization long-range industrial pollutant transport. However, odour is human's subjective response to odorants (chemical substances), and odour concentration is quantified as OU (odour unit) or OU/m^3 measured by dilution to detection threshold (DT), the dilution ratio of clean air to the odorous sample air to the level at which odour can be just detected by 50% human panellists. For most of applications of air dispersion models, odour concentration employs the unit of OU/m^3, which corresponds to the mass concentration unit of g/m^3. Nevertheless, odour emission from CAFOs varied greatly from the emission from industrial sources in the following aspects:

• Constituents

Pollutants emitted from industrial sources are carbon dioxides, nitrogen oxides, sulphur oxides and particulate materials etc. resulted mainly from fossil-fuel burning or other chemical reactions. Whereas odour emissions from CAFOs consists of up to 300 chemical compounds including NH3, amines, sulphides, volatile fatty acids, alcohols, aldehydes, mercaptans, esters, and carbonyls resulted mainly from anaerobic decomposition of manure (Sweeten, 2002).

• Characteristics

The regulatory process for industrial sources specifies a series of standards that the concentrations of the pollutants are not exceeded. Whereas odour is a human olfactory response to odorants, nuisance of odour is quantified by the following characteristics: 1) the concentration, 2) the intensity, 3) the frequency, 4) the duration, and 5) hedonic tone (Sweeten, 2002).

• Source emission

The industrial sources (stack) are commonly featured by up to several hundreds meters height, high emitting temperature, and high emitting velocity. Whereas the sources of livestock odour are of ground level, low emitting temperature and low emitting velocity.

• Travel distance

Traditional dispersion models predict downwind concentration of pollutants emitted from industrial sources from several kilometres up to 50 km (short range), or from 50 km up to several hundreds kilometres (long range). Whereas livestock odour is diluted very quickly when transported by wind, so the typical setback distance recommended by current regulatory guidelines is around 0.4 to 3 km (Guo et al., 2004).

• Model computational time interval

Most of the Gaussian-based models (e.g. ISCST3, CALPUFF, AERMOD, and AUSPLUME) are designed to use hourly meteorological data. The models are intended to calculate the averages over the period of hours, days, and up to years. It is assumed that the hour-average meteorological data including wind speeds and direction remain steady in the hour of calculation. The diluting effects of constant changing of wind speed and direction are ignored in the models with hourly time interval.

Zwicke (1998) reported that ISCST3 with 1 h time interval over-predicted the concentrations by 2.5 to 10 times compared with test results by a series of controlled pollutant release and measurement. Fritz et al (2005) also found that the appropriate time interval for Gaussian-based dispersion models varied widely depending on the corresponding meteorological variations, and using 1 h time interval might result in overestimated downwind concentrations. Using four air dispersion models for livestock odor dispersion simulation, Xing et al. (2006) found that livestock odor can travel much farther under steady state meteorological conditions than using variable meteorological data and concluded different odor concentration criterion should be used for setback distance determination for using steady-state or variable meteorological data.

Application of traditional dispersion models with hourly meteorological data has been proved inaccurate for predicting downwind odour dispersion from CAFOs. Zhu et al. (2000) and Guo et al. (2001) used scaling factors of 10 for manure storage sources and 35 for livestock building sources to amplify the source odor emissions for input into INPUFF-2 model in order to adjust the modeled results to the same numerical magnitudes of the field measured odour concentrations. Zhou et al. (2005) and Xing et al. (2006) predicted downwind odour concentration from two swine farrowing facilities using several industrial air dispersion models. Prediction results with 1 h time interval were compared with three 10-min sessions in field measurements by 15 trained human sniffers. It was found that all models' predictions had low agreement with field measured odour concentrations (28 to 35%) if excluding the measurements with intensity zero (no odour). Furthermore, the 1 h time interval odour prediction results by most of Gaussian-based dispersion model are not capable of characterizing odour frequency and/or duration. The National Center White Papers of the United States have identified the development of accurate dispersion models for livestock odours for specific types of CAFOs as an urgent research need (Sweeten, 2002).

Computational Fluid Dynamics (CFD) model have been explored to predict odour dispersion from livestock facilities (Bjerg et al. 2004; Li et al. 2006). CFD method numerically solved the basic governing equations of mass, momentum, and energy within each cell in a discretized modeling domain. The method employed Eulerian-Lagrangian approach to simulate dispersion in planetary boundary layer (PBL). Eulerian-Lagrangian approach solved turbulent air flow within Eulerian reference frame, and then calculated trajectories of discrete particles in continuous flow field within Lagrangian reference frame (Li et al., 2006). The time interval is determined in CFD time–dependant calculation as time step ranged from sub-second to hours. Therefore, it is very convenient for CFD method to use sub-hour meteorological data and evaluate the effects of variation of time intervals on odour dispersion. Many commercial CFD packages, CFX, FLUENT, STAR-CD, and CFD2000 et al. are available now and are extensively applied into the study of atmospheric dispersion in rural and urban areas (Baik et al., 2003, Pospisil, et al. 2004; Riddle et al., 2004; Pullen, et al. 2005; Brown, et al. 2005; Scargiali, et al. 2005). Bjerg et al. (2004) applied FLUENT 5 (Fluent Inc., Lebanon, N.H.) to predict the dispersion of exhausted odorous air from a commercial growing-finishing pig building in Denmark. Comparison with the full scale tracer gas measurements indicated that CFD method was a suitable technique to predict the spreading of odorous emission 50 to 150 m from livestock building. Li et al. (2006) applied FLUENT 6 predicted downwind odour dispersion up to 5 km from a swine barn and earthen manure storage under 30 meteorological conditions. CFD prediction results were compared with the results obtained by CALPUFF model. Comparisons showed that odor concentration predicted by CFD model were higher than those made by CALPUFF model in short distances (<300 m). Beyond that, CFD predictions were higher than CALPUFF predictions under categories A, B, C, and D, and lower under category F

The objective of this study is to use CFD dispersion model to predict odour dispersion for a commercial swine farrowing operation with Eulerian-Lagrangian approach and to evaluate the effects of time interval on odour dispersion prediction.

MATERIALS AND METHODS

Site descriptions

A farm of 3000-sow farrowing operation, located in southern Manitoba, Canada was selected in this study. The farm had a barn (176 m × 31 m) and an open single cell earthen manure storage (EMS) (254 m × 43 m). They are all along the west-east direction and the EMS located closely at the north of the barn. The barn was mechanically ventilated with 84 wall-mounted exhaust fans. Liquid manure was stored in under-floor shallow gutters and removed to outdoor EMS once every three weeks. The surroundings of the farm were flat cropland. Detailed farm descriptions were given by Zhang et al. (2005). The average odor emission rates were 129,267 (OU/s) for the barn and 191,923 (OU/s) for the EMS (Zhang et al., 2005), which were used in this study

Meteorological data processing

CFD model calculated downwind odour concentration in terms of the source information and meteorological data in time interval of Δt. Weather variables including solar radiation, air temperature, relative humidity, wind speed and direction were taken every minute by the on-site weather station (WatchDog Model 550, Spectrum Technologies Inc., Plainfield IL). The original on-site measured data were processed by Meteorological Processor for Regulatory Models (MPRM), a general purpose program used to process meteorological data in US EPA recommended air quality dispersion models (US EPA, 1996). Capabilities of MPRM include quality assessment of meteorological data, detailed report generation, and the ability to process a variety of meteorological data bases including both on-site and National Weather Service (NWS) meteorological data. The tasks of MPRM processing in this study were focused on classification of atmospheric stability and generalization of meteorological data with Δt= 1, 10, 20, 30, and 60 min time intervals from on-site 1 min measured data.

MPRM employed many methods to estimate atmospheric stability. In this study, atmospheric stability was classified using the solar radiation delta-T (SRDT) method for estimating Pasquill-Gifford (P-G) stability categories (US EPA, 2000). P-G stability categories include six categories corresponding to different meteorological conditions (Pasquill, 1971): A (strongly unstable), B (moderately unstable), C (slightly unstable), D (neutral), E (slightly stable), and F (moderately stable). SRDT method (Table 1) used wind speed in combination with measurements of total solar radiation during the day and a vertical temperature difference at night to classify stability category (US EPA, 2000).

MPRM calculated values of weather variables in certain time interval as the arithmetic means for most variables except for wind speed and direction. For the sequence of N observations of wind speed u_i and wind direction θ_i, ($i \leq n$, $0<\theta_i \leq 360$), Vector computation in MPRM generated the mean east-west component of wind speed V_e, and north-south component V_n with the following equations:

$$V_e = -\frac{1}{N}\sum_{i=1}^{N} u_i \cdot \sin\theta_i \tag{1}$$

$$V_n = -\frac{1}{N}\sum_{i-1}^{N} u_i \cdot \cos\theta_i \tag{2}$$

The resultant wind speed U_{av} (m/s) and direction θ_{av} (Deg) during the given time interval are generated as the following equations:

$$U_{av} = (V_e^2 + V_n^2)^{\frac{1}{2}} \tag{3}$$

$$\theta_{av} = ArcTan\,(V_e / V_n) \pm 180 \tag{4}$$

where + 180 is applied when ArcTan (V_e/V_n) < 180, and -180 if ArcTan (V_e/V_n)>180.

The on-site measured meteorological data in between 14:00-15:00 on June 29th, 2004 were selected for CFD modeling in this study. The measured wind speed during the period ranges from 3.1 to 7.6 m/s. The wind direction in the first 20 minutes was mainly from the east to the west. During the last 40 minutes, the wind changed to the opposite direction roughly from the east to the west. The total of 60 meteorological datasets in 1 hour were directly input to CFD model for the calculation of odour concentration in each minute. The meteorological data with Δt =10, 20, 30, and 60 min time intervals were synthesized by MPRM from on-site meteorological data (Table 2). For example, 6 weather data sets with Δt =10 min time interval were separately synthesized from the meteorological data during each 10 min period in the given hour. Similarly, for Δt = 20, 30, and 60 min, the number of datasets were 3, 2, and 1, respectively. The datasets with different time interval were input into CFD model to evaluate the effects of the length of time intervals on odour prediction.

CFD dispersion model

Commercial CFD package FLUENT version 6.1 (Fluent Inc., Lebanon, N.H.) were used in this study. CFD method numerically solves the basic governing equations in conservation form in discretized domain. The first step in CFD modeling is the determination of modeling domain. In this study, a full three-dimensional cylinder with a 5000 m radius ground plane and 200 m height was constructed as CFD modeling domain for odor dispersion. The barn and the EMS were located at the center of ground plane. The modeling domain was then divided into 16 wedge-shaped parts in accord with the meteorological definition of wind directions. The wedge-shaped divisions were very convenient for wind direction configuration in boundary conditions. The domain was discretized by non-structural grid strategy. There were a total of 200,000 cells in the CFD modeling domain in this study. All the geometrical body constructions in the modeling domain and grid generation were completed in GAMBIT (geometry and mesh building intelligent toolkit), a pre-processor for the CFD commercial software FLUENT.

A Lagrangian discrete phase model (LDPM) driven by large eddy simulation (LES) turbulent flow field was presented in CFD model to predict downwind odour concentrations. This Eulerian-Lagrangian approach solves continuous air flow in Eulerian reference frame and then solves trajectories of discrete particles in Lagrangian reference frame. Discrete "odorous gas parcels" (OGPs) is used in Eulerian-Lagrangian approach rather than sensations because it is physical odorants that are dispersed. The surface of the EMS and the areas of wall-mounted exhaust fans were treated as surface injection types in FLUENT. OGPs were continuously released from the injection surfaces with specific velocity and temperature (Li et al. 2006). The measured odor emission rates for the barn and the EMS were input in FLUENT as injection flow rates with the unit defined as OU/s, corresponding to mass concentration of g/s. OGPs were defined as very tiny particles with 10^{-6} m diameter. The number of emitted OGPs emitted was determined by injection flow rate and particle diameter and was calculated automatically by FLUENT.

After released from the injection surfaces, the OGPs were neutrally buoyant and moved with the wind. The changes in the speed and direction of the OGPs followed the instantaneous wind speed and direction. Odour concentrations within the domain were represented by calculations of the trajectories of all parcels in the domain except those that escaped and aborted. The odour concentrations at the receptors were exported from FLUENT by the function of discrete phase concentration. The height of receptors was 1.5 m above the ground, which was the nose height of the receptors (Li et al. 2006).

Wind and temperature profile in modeling domain are very important to odour dispersion. The profiles are initialized with User Define Functions (UDF) programmed by C code and compiled in FLUENT at the beginning of the iteration. Wind speed increases with altitude in PBL according to the power law relationship. The power law exponent p depends on atmospheric stability category, as given in Table 3 (Heinsohn et al., 1999).

The negative temperature gradient in the atmosphere is called lapse rate (LR) and reflects meteorological turbulent conditions classified by atmospheric stability categories. A neutral condition is defined as one in which the lapse rate is equal to the dry adiabatic rate (DAR) of 9.8 K/km, while a stable condition has a lapse rate less than DAR, and a unstable condition with a lapse rate higher than DAR. In this study, air temperature vertical profile was configured in CFD model by the lapse rate according to Pasquill stability categories.

RESULTS AND DISCUSSIONS

Odour dispersion from the 3000-sow farrowing operation in south Manitoba at 14:00-15:00 on June 29th 2004 was predicted with different meteorological time intervals: 1, 10, 20, 30, and 60 min. It was assumed that the weather variables remained stable throughout each time interval. For example, for Δ t = 1 min calculation, the weather variables including wind speed and direction remained stable during each minute and then changed in the next minute. Similarly, for

$\Delta t = 10$, 20, 30, and 60 min calculations, the weather variables remained stable during each of the 10, 20, 30, and 60 minute time intervals in the given hour, respectively. Odour concentration predicted with different time intervals were compared at the receptors' locations, 1.5 m above ground, which was the nose height of the receptors.

Figure 1 presents odour contour at 10 min after odour was emitted from the sources predicted by CFD model with $\Delta t = 1$ and 10 min. During this first 10 min, wind blew mainly from east to west (100 ^{o}) and varied slightly (standard deviation 18 ^{o}). Odour plume predicted with $\Delta t = 1$ min was emanative due to meandering effect by the wind direction variations. The width of odour plume was greater than that with $\Delta t = 10$ min at all distances from the sources. Odour plume predicted with $\Delta t = 10$ min was congregated in a narrow corridor. For the same odour emission rate, the larger the area odour dispersed, the lower the downwind odour concentration would be. Figure 2 shows the downwind odour concentration predicted with $\Delta t = 1$ and 10 min. For time interval $\Delta t = 10$ min, downwind odour concentration were collected at the receptors along the centre line of the odour plume, i.e. the maximal odour concentration at each given distance from the source. Unlike the clear centerline observed with $\Delta t = 10$ min, odour plume with $\Delta t = 1$ min was scattered due to wind direction variations and no centerline was observed. Therefore for predictions with $\Delta t = 1$ min, odour concentration of the receptor with the maximum value for each distance was selected as downwind odour concentration at that distance from the sources (Fig. 2). In general, odour concentration predicted with both time intervals decreased gradually with the increase of distance from the sources. The odour concentration predicted with $\Delta t = 1$ min fluctuated with the distance. For most of the downwind receptors, odour concentration predicted with $\Delta t = 10$ min were greater than that with $\Delta t = 1$ min. Meanwhile, there were much difference for odour travel distances between predictions with $\Delta t = 1$ min and 10 min. Odour travel distance predicted with $\Delta t = 10$ min for achieving 5 OU/s was 3310 m comparing with 2910 m, as predicted with $\Delta t = 1$ min.

Odour contours and the maximal downwind concentration at t = 20 min predicted with time interval $\Delta t = 1$, 10, and 20 min were presented in Figs. 3 and 4. For predictions with $\Delta t = 1$ min, odour were spread to much larger area than that with time interval $\Delta t = 10$ and 20 min. The shapes of the odour plumes were similar for the predictions with time intervals $\Delta t = 10$ and 20 min. Odour concentrations predicted with time interval $\Delta t = 10$ min were less than that with time interval $\Delta t = 20$ min while the predictions with $\Delta t = 1$ min were the lowest at all distance from the sources (Fig. 4). Odour travel distance was the farthest for prediction with $\Delta t = 20$ min. Distance for odour concentration achieving 5 OU/m^3 was 4650 m for predictions with $\Delta t = 20$ min, 3750 m for $\Delta t = 10$ min, and 3720 m for $\Delta t = 1$ min.

Fig. 5 showed odour contours predicted by CFD model with $\Delta t = 1$, 10, and 30 min at t =30 min of the given hour. Wind direction changed to opposite direction from east to west after t = 20 min. The downwind odour plume in the first 20 min became upwind and influenced downwind odour concentration after 20 min due to wind direction shift. The effect of upwind odour plume was very obvious in predictions with $\Delta t = 1$ min, and had less influence on the predictions with $\Delta t = 10$ min. The effect was not found on the predictions with $\Delta t = 30$ min because of the application of average meteorological data during this 30 min time period. The averaged weather variables ignored the wind direction shift during the period. Therefore orientation of the odour plume predicted with Δ t = 30 min was completely different with predictions with Δ t = 1 and 10 min. Odour concentration predicted with Δ t = 1 min were higher than that with Δ t = 10 and 30 min close to the sources (< 3000 m) due to the effect of upwind odor plume (Fig. 6). Beyond that, odour concentration decreased very rapidly. For the same distance from the sources, odour concentrations with long time interval (Δ t = 30 min) were higher than that with short time interval (Δ t = 10 min). Prediction with Δ t = 1 min were more sensitive to wind direction shift and provided more accurate instantaneous odour plumes than Δ t = 10 and 30 min.

Odour concentrations predicted with Δt = 1, 10, 20, 30, and 60 min were compared at the end of the given hour (15:00). Comparing odour plume predicted with various time intervals, orientation and shape of odour plume predicted with Δt = 60 min was different from the other predictions because the hourly meteorological data were used (Fig. 7). The variations of wind direction in the given hour were not considered in the prediction with Δt = 60 min. The maximal odour concentrations within 5 km predicted with 1 h time interval were the highest at the almost of all distances (Fig. 8), indicating that predictions with 1 h time interval overestimated downwind odour concentrations compared with the prediction with sub-hour time intervals. Odour concentration predicted with Δ t = 1 min fluctuated at the short distance and then decreased very rapidly. For most of the receptors in the given hour, the longer the time interval, the higher the odour concentration would be. Figure 9 showed travel distance for odour concentration achieving 5 OU/m^3 at the end of the given hour. Although travel distance predicted with Δ t = 1 min was slightly higher than that with Δ t = 10 min, generally the longer the time interval, the longer odour travel distance would be.

CONCLUSIONS

A CFD model with Eulerian-Lagrangian approach was applied to predicted odour dispersion from a 3000-sow farrowing operation in southern Manitoba, Canada. The on-site measured weather variables were synthesized into meteorological data with time intervals 1, 10, 20, 30, and 60 min by Meteorological Processor for Regulatory Models (MPRM). Downwind odour concentrations predicted with different time intervals were compared to evaluate the effects of model computational time interval on odour dispersion.

Predictions with 1 h time interval overestimated downwind odour concentration compared with the predictions with sub-hour time intervals. The longer the time interval, the higher the odour concentration would be downwind from the sources. Meanwhile, the same tendency was found in the predictions of odour travel distance, longer odour travel distance was predicted with longer time interval. Variations of wind direction influenced downwind odour dispersion greatly. However, model predictions with long time interval used meteorological data averaged in a long time interval and neglected the variations of wind direction during each time interval. Model predictions using short time intervals (e.g. Δ t = 1 min) were more sensitive to wind direction shift and provided more accurate instantaneous odour plumes than longer time intervals. The challenge of application short modeling time interval is the requirement for more refined meteorological data in the modeling.

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Table1. Solar radiation delta-T (SRDT) method for estimating Pasquill-Gifford (P-G) stability categories (US EPA, 2000)

Day time				
Wind Speed (m/s)	Solar Radiation (W/m2) ≥ 925	925 – 675	75 – 175	< 175
< 2	A	A	B	D
2 - 3	A	B	C	D
3 - 5	B	B	C	D
5 - 6	C	C	D	D
≥ 6	C	D	D	D
Night time				
Wind Speed (m/s)	Vertical temperature gradient < 0	≥ 0		
< 2.0	E	F		
2.0 - 2.5	D	E		
≥ 2.5	D	D		

Table2. Meteorological data in different time intervals synthesized by MPRM from on-site measurement data in south Manitoba. (SR: solar Radiation; T: temperature; RH; relative humidity; WD: wind direction; WS: wind speed; SC: stability category; SD: standard deviation for wind direction)

Time (6/29/2004)	SR (W/m^2)	T (◦ C)	RH (%)	WD (Deg)	SD (Deg)	WS (m/s)	SC
Meteorological data in 10 minutes time interval							
14:00-14:10	862	29.9	22	100	18	5.3	C
14:10-14:20	864	29.9	22	96	19	5.3	C
14:20-14:30	874	30.4	22	256	40	5.2	C
14:30-14:40	883	30.4	22	258	6	5.0	B
14:40-14:50	881	30.2	23	268	18	4.9	B
14:50-15:00	741	30.3	23	257	9	4.7	B
Meteorological data in 20 minutes time interval							
14:00-14:20	863	29.9	22	98	19	5.3	C
14:20-14:40	878	30.4	22	257	29	5.1	C
14:40-15:00	811	30.2	23	263	15	4.8	B
Meteorological data in 30 minutes time interval							
14:00-14:30	866	30.1	22	112	77	5.3	C
14:30-15:00	835	30.3	23	261	13	4.8	B
Meteorological data in 1 h time interval							
14:00-15:00	851	30.2	22	238	78	5.1	C

Table3. Power law exponent p for different atmospheric stability categories in rural area (Heinsohn et al., 1999)

Category	A	B	C	D	E	F
Value p	0.07	0.07	0.10	0.15	0.35	0.55

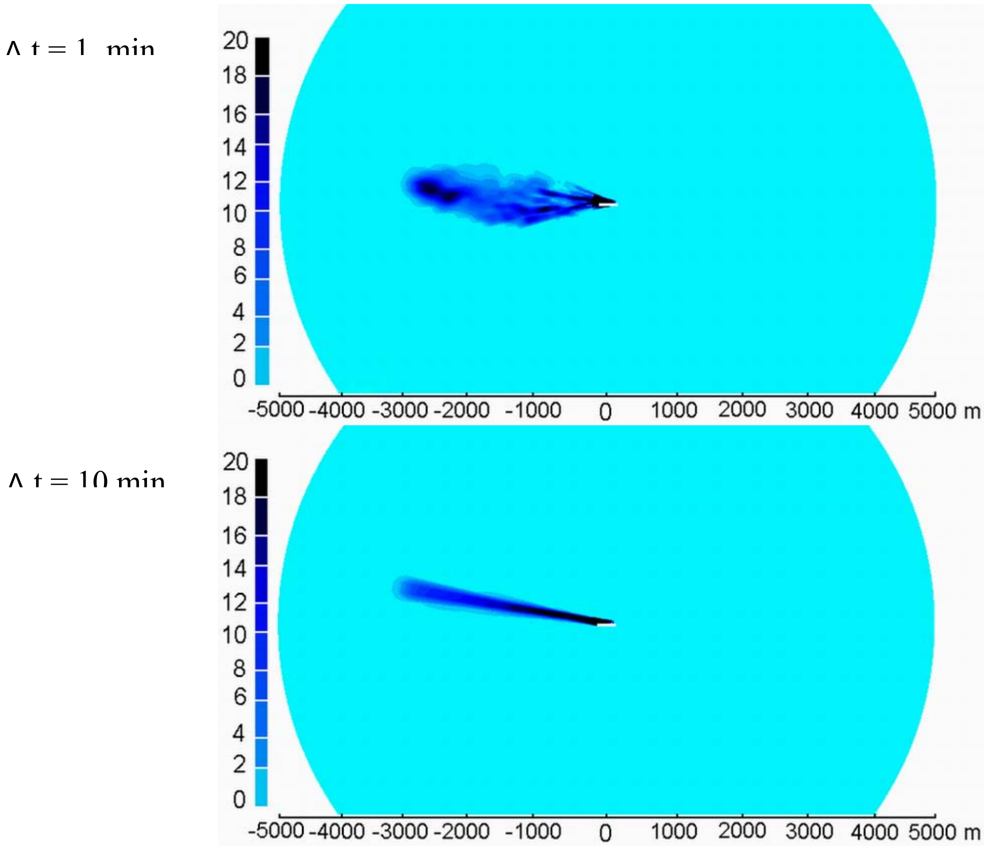


Figure 1. Odour contours at t = 10 min predicted with time intervals Δ t = 1 and 10 min

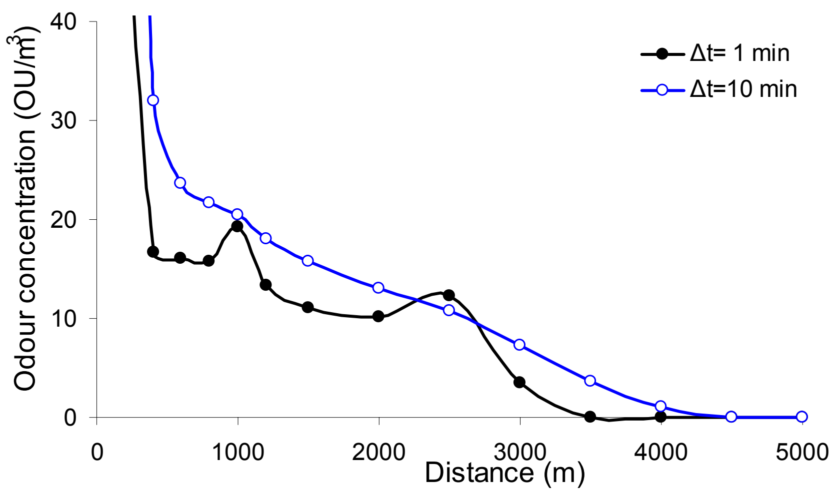


Figure 2. Comparison of downwind odour concentration predictions at t = 10 min

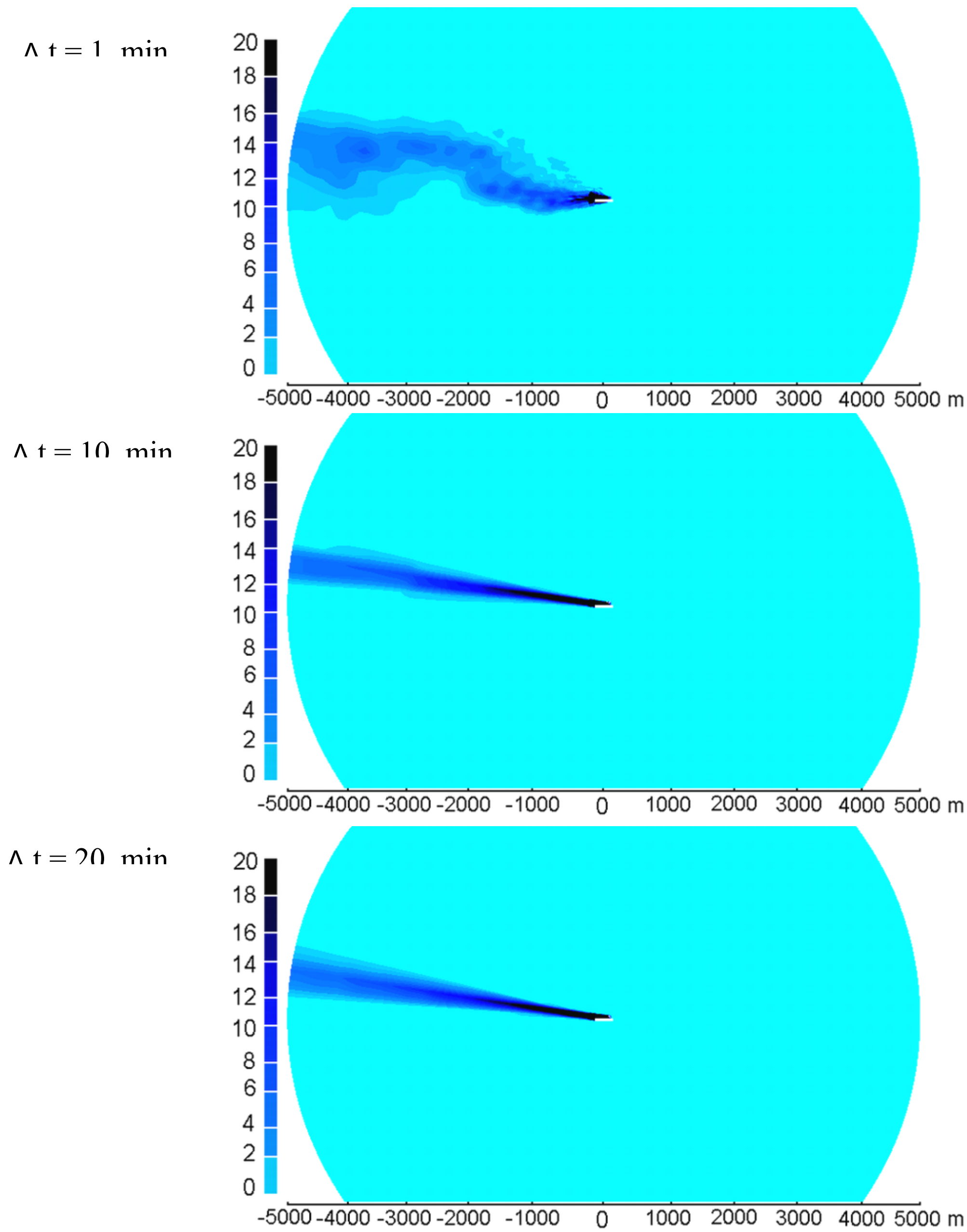


Figure 3. Odour contours at t = 20 min predicted with time intervals Δ t = 1, 10, and 20 min

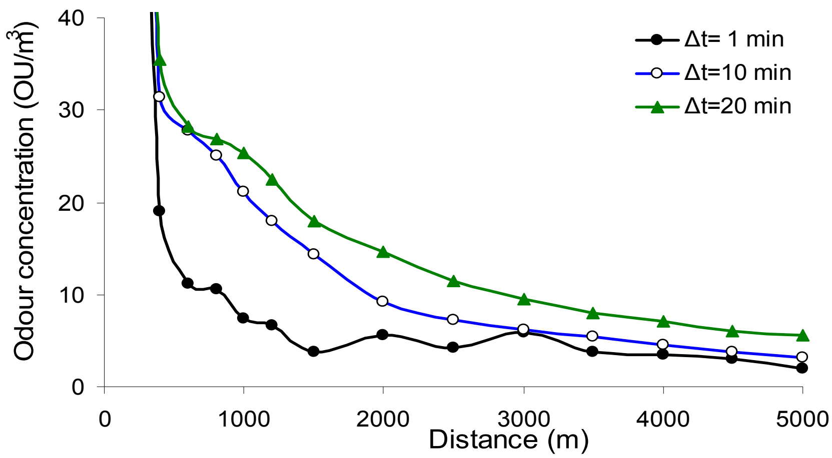


Figure 4. Comparison of downwind odour concentration predictions at t = 20 min

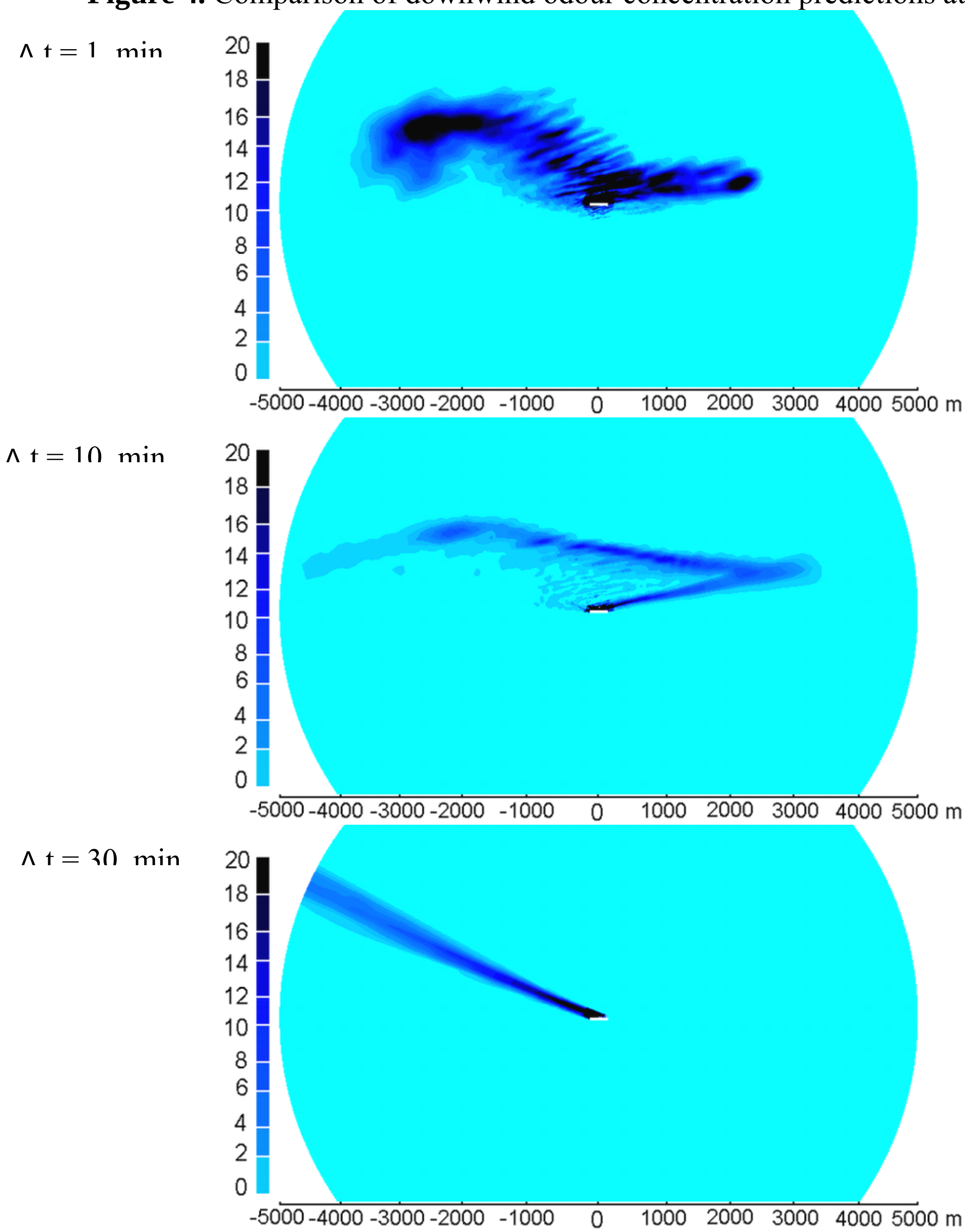


Figure 5. Odour contours at t = 30 min predicted with time intervals Δ t = 1, 10, and 30 min

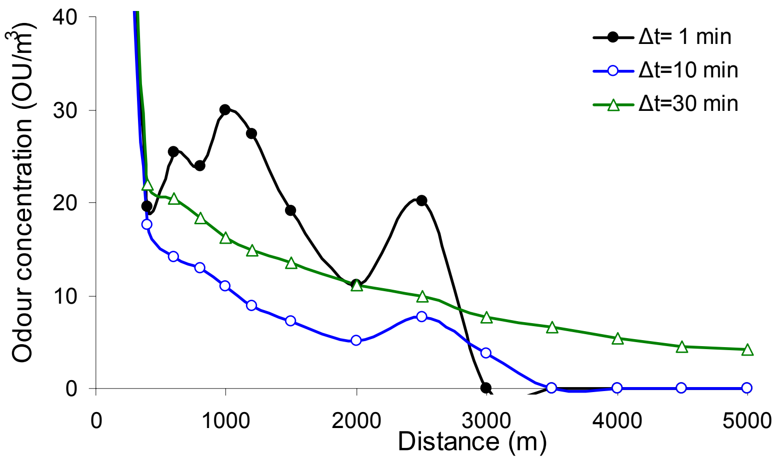
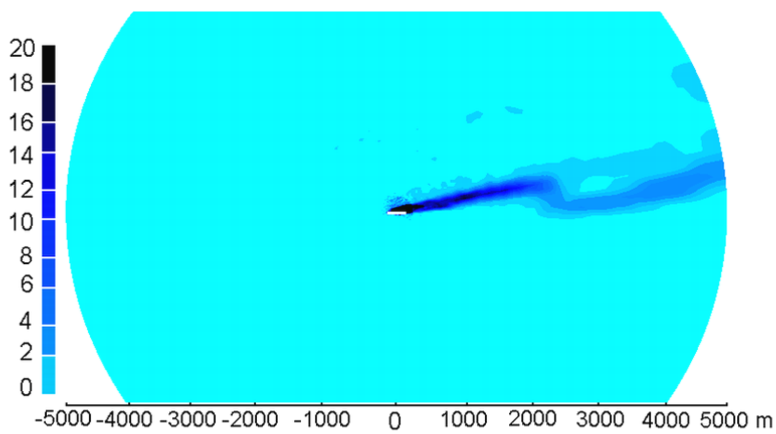
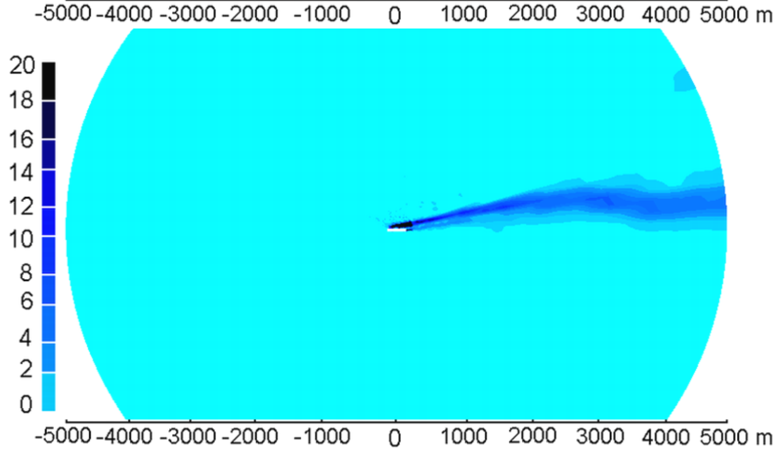


Figure 6. Comparison of downwind odour concentration predictions at t = 30 min

Δ t = 1 min



Δ t = 10 min



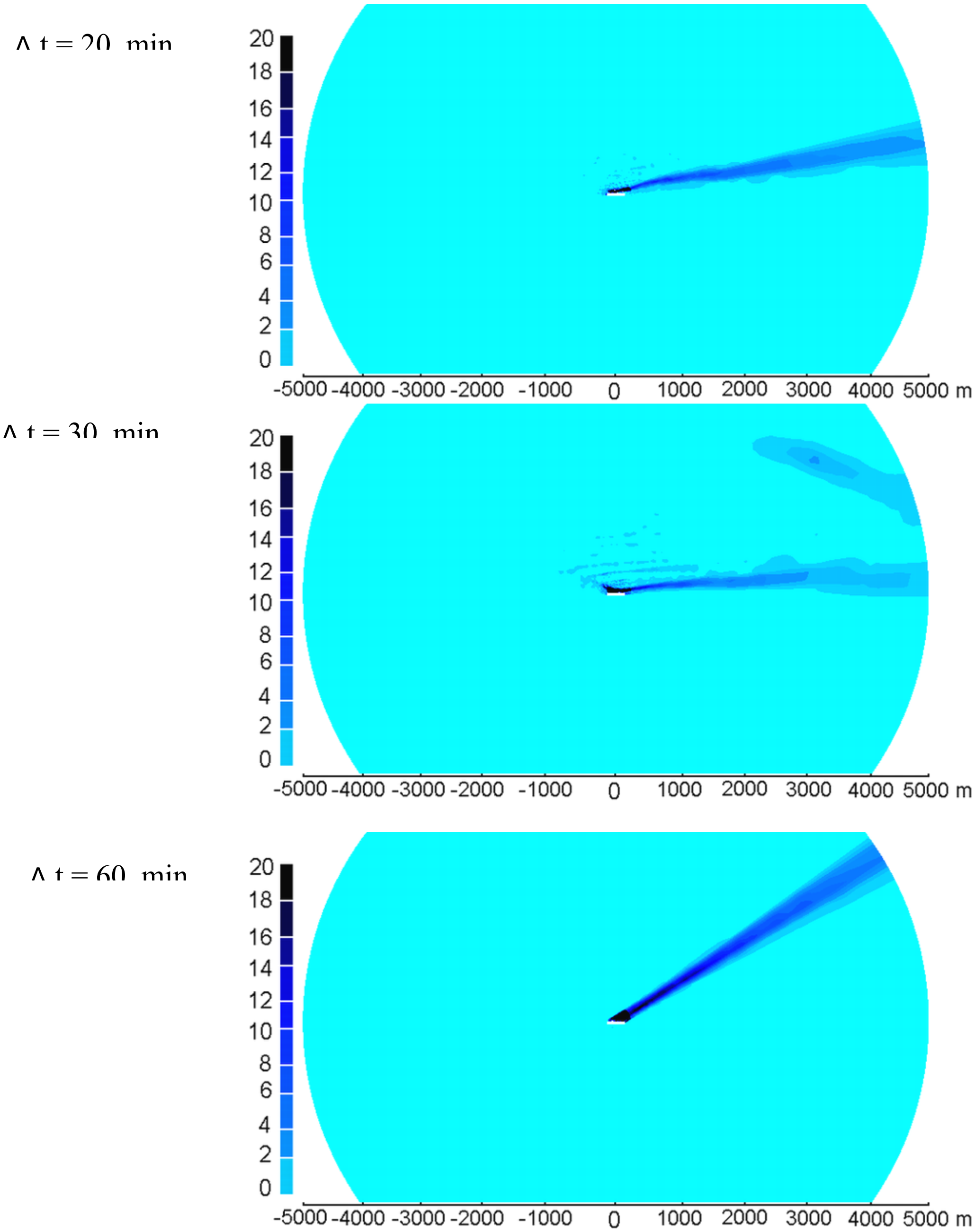


Figure 7. Odour contours at the end of the given hour predicted with time intervals Δ t = 1, 10, 20, 30, and 60 min

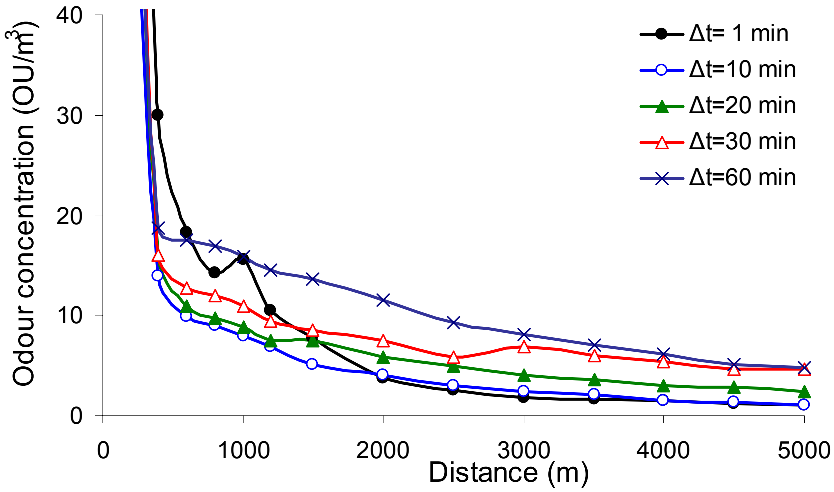


Figure 8. Comparison of downwind odour concentration predictions at the end of the given hour

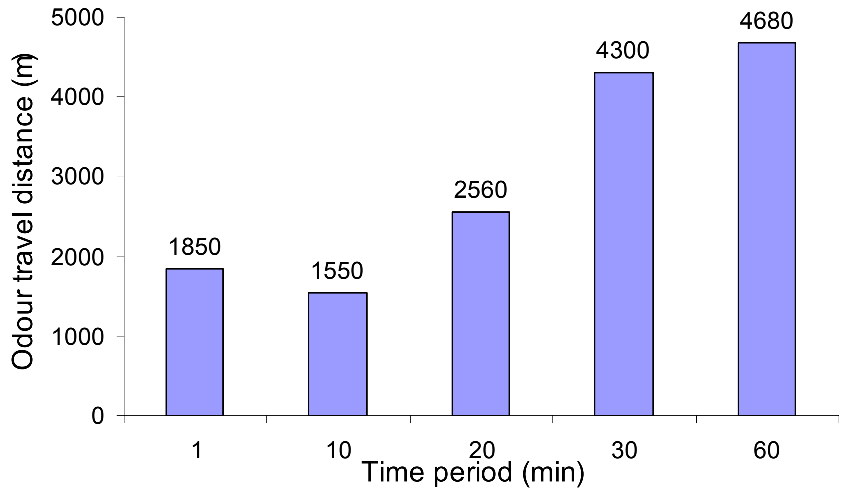


Figure 9. Odour travel distance for achieving 5 OU/m^3 predicted with different time interval at the end of the given hour