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Role of Correlation among Physical Factors in Probabilistic Simulation of Emissions of Volatile Organic Compounds from Floating Storage and Offloading Vent Stack

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ABSTRACT

This research investigated the roles of correlations among physical factors in the probabilistic simulation of volatile organic compounds (VOCs) emitted from a marine vessel (known as floating storage and offloading, FSO), located in the Gulf of Thailand. The physical factors in this study were wave height, ambient temperature, storage temperature, storage quantity, Reid vapor pressure, and the daily incoming rate. These physical factors were transformed into normally distributed data and a second-order multiple linear regression (MLR) with interaction effects, that were then used to determine the relationship between the transformed physical factors and the VOC venting volume from the FSO. The dataset of relevant predictors (transformed physical factors and interactions) that provided the maximum adjusted coefficient of determination was chosen for inclusion in the MLR. After that, two datasets of 1,000 venting volumes (one with and one without correlations among physical factors) were simulated. In the simulation, 1,000 datasets of six physical factors were generated according to observed averages and standard deviations. Cholesky randomization was used to generate the correlated physical factors for the simulation with correlation among physical factors. The averages of VOC venting volumes calculated from the generated physical factors when correlations among physical factors were and were not applied were 211,610 and 210,906 ft^3, respectively (observed average was 210,984 ft^3), with standard deviations of 38,828 and 40,787 ft^3, respectively (observed standard deviation was 67,961 ft^3), and skewness values of 0.74 and 0.51, respectively (observed skewness was 0.71). Therefore, correlation among the physical factors improved the skewness and provided better simulation results for VOC emission.

1. INTRODUCTION

Volatile organic compounds (VOCs) contribute to the formation of tropospheric ozone, which causes negative impacts on human health and the environment (Shao et al., 2020). Under normal atmospheric conditions, the VOCs emitted from natural gas liquids (NGLs) comprise 2.63% ethane, 14.60% propane, 14.87% butane, 1.96% pentane, 0.26% hexane, and 0.17% heptane (Seekramon, 2015; Drysdale, 2019). While operating a marine vessel, called floating storage and offloading (FSO), the increase in incoming NGLs into the storage tank raises the internal pressure, leading to VOC evaporation and accumulation in the tanks. The accumulated VOCs are eventually released to the atmosphere via the FSO vent stack to prevent an explosion and deformation of the FSO storage tanks (Seekramon, 2015; Vos et al., 2007). VOCs are key factors in forming ozone and fine particulates in the atmosphere. Human exposure to such pollutants at high concentrations over extended

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periods has long-term adverse health effects, such as prolonged eye, nose, and throat irritation among the exposed workforce (Mo et al., 2021).

It has been reported that VOC emissions from storage tanks were associated with several physical factors relating to the NGLs and/or oil products and operating conditions, including Reid vapor pressure (RVP), storage quantity, storage temperature, product incoming rate, and turbulence from NGLs or oil movement (Rudd and Hill, 2001). Additionally, the VOC emission from an FSO tank is affected by ambient conditions (Alam et al., 2019), including solar radiation, ambient temperature, and turbulence from wave height (Hu et al., 2020; Lin et al., 2009; Yang et al., 2017; Lang et al., 2017). However, there has been no integrated investigation of these physical factors and applied probabilistic simulation to predict the VOC emission.

Probabilistic simulation is a statistical technique for exploring the impact of uncertainty in data (Alshanbari et al., 2023). In a probabilistic simulation, various inputs are used to calculate the outputs under different probabilities. Lynd and O'brien (2004) used a second-order Monte Carlo simulation to estimate disease risks to produce a risk-benefit acceptability curve. Cao et al. (2013) used a probabilistic simulation to model oil spilled concentration based on time, magnitude, and location. The obtained simulation was used to quantify risk analysis and to support a comprehensive spill management framework. Lin et al. (2022) used probabilistic simulation to estimate the exposures and risks of indoor VOCs and formaldehyde based on their concentrations, inhalation rates, exposure frequencies, and the body weights of the receptors. The current study used probabilistic simulation to predict the VOC venting volume based on various physical factors during the FSO operation. Typically, the physical factors are correlated with each other. Therefore, the simulation result may be inaccurate if such correlations are ignored. Thus, simulation with correlation among physical factors can produce more accurate results.

In this study, six physical factors (wave height, ambient air temperature, storage temperature, storage quantity, RVP, and daily incoming rate of the NGLs) were used in the probabilistic simulation of the venting volume associated with VOC emission. In addition, the role was investigated of correlations among these physical factors in probabilistic simulation. The results from this study can be applied to simulate the venting volume of VOC-contained gas from the FSO stack under different probabilities, which, in turn, would be useful for many purposes, especially those involving risk assessment.

2. METHODOLOGY

2.1 Data gathering and screening

The data used in this study consisted of the VOC venting volume from the stack of an FSO in the Gulf of Thailand and six relevant physical factors influencing the venting volume (wave height, ambient temperature, storage temperature, storage quantity, RVP, and daily incoming rate of the NGLs). Wave heights were collected using a wave buoy (Fugro; Norway). Data were collated 100 times per day but only 33 middle-range data out of 100 daily wave height data were used to calculate the average and reported as daily wave height. Ambient temperatures were measured using temperature sensors (PT100; SMA Solar Technology; Germany). Storage temperature was measured using a temperature sensor and storage quantity was measured based on a radar beam method. These instruments were included in the tank monitoring system (Kongsberg GL-300; Norway). The daily incoming NGL rate was calculated as the difference between the storage quantities on 2 consecutive days. RVP was defined as the absolute vapor pressure of the liquid at 37.8 ºC (100 ºF). Its value was obtained based on the ASTM-D323 test method, using the Holler Bomb Test (Koehler Instrument Co. Ltd.; USA). The VOC venting volume from the stack of the FSO was measured daily using an ultrasonic flare gas flow meter (GF868; GE; USA). This instrument was installed on the vent stack of the FSO. These data were collected throughout 2020. However, the data on the VOC venting volume on some days might be discontinuous due to closure of the vent stack during bad weather or stack maintenance, resulting in less venting volume than usual. For this reason, venting volume data of less than 90,000 ft^3 were excluded from this study.

2.2 Determination of relationship between physical factors and venting volume

Multiple linear regression (MLR) is a statistical technique that can be used to analyze the relationship between the physical factors and venting volume. However, since this research conducted probabilistic simulation and Cholesky randomization, one of the steps of probabilistic simulation requires the inputs to be normally distributed. Therefore, the data on physical factors were transformed for normality before determining the relationship.

2.2.1 Two-step normality transformation

Two-step normality transformation was applied to transform each physical factor for normality (Templeton and Burney, 2017). First, the data were transformed for uniformity. In this step, the data of each physical factor were converted to a percentile rank (Equation 1) and uniformly distributed:

$$\text{Percentile Rank}\ (X_i) = \frac{\text{Rank}(X_i)}{100(n+1)} \quad (1)$$

Where; X_i is the i^{th} smallest data, $\text{Percentile Rank}\ (X_i)$ is the percentile rank of X_i, $\text{Rank}(X_i)$ is an ascending rank of X_i, and n is the count of data.

The second step was a transformation of data from uniformity to normality. In this step, the inverse normal distribution was used to convert the percentile ranks (resulting from the first step) to provide normally distributed z-scores (Equation 2):

$$p = \mu + \sqrt{2}\ \sigma\, \text{erf}^{-1}(-1 + 2P_r) \quad (2)$$

Where; p is the transformed data, μ is the mean of the data, σ is the standard deviation of the data, erf^{-1} is the inverse of the error function, and P_r is a probability calculated from the percentile rank.

2.2.2 Second-order multiple linear regression with interaction effects and selection term of terms and measurement of accuracy

MLR was used to predict the VOC venting volume from the six independent variables (transformed wave height, transformed ambient temperature, transformed storage temperature, transformed storage quantity, transformed RVP, and transformed daily incoming rate). Since the effect of each independent variable may vary, the relationships between the VOC venting volume and the independent variables were determined based on a second-order MLR with interaction effects, as shown in Equation 3 (Cho and Lee, 2018; Jia et al., 2020):

$$Y = a + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} \sum_{j=i}^{n} c_{ij} x_i x_j \quad (3)$$

Where; Y is the VOC venting volume, a, b_i, and c_{ij} are constants, n is a number of factors, and x_i and x_j are the values of i^{th} and j^{th} independent variables, respectively.

Since not all interaction effects were necessary for the prediction of the VOC venting volume, the adjusted coefficient of determination (adjusted R^2) was calculated to determine the usefulness of each term in the MLR. The adjusted R^2 was calculated using Equation 4 (Alam et al., 2019; Pham, 2019):

$$R^2_{adj} = 1 - (1 - R^2)\left(\frac{n-1}{n-p-1}\right) \quad (4)$$

Where; R^2_{adj} is the adjusted coefficient of determination (adjusted R^2), R^2 is the coefficient of determination, n is the number of data, and p is the number of predictors.

The terms in the MLR were selected by maximizing the adjusted R^2. In other words, only the terms that improved the value of the adjusted R^2 were included in the MLR. After the selection of terms, the root mean squared error (RMSE) and coefficient of determination (R^2) were calculated to evaluate the accuracy of the MLR. Finally, the significance of each term in the MLR was appraised based on a t-test at a significance level of 0.05 (Cho and Lee, 2018).

2.3 Probabilistic simulation of venting volume

Probabilistic simulation was used to generate different values of the venting volume. First, the average and standard deviation of each physical factor were calculated, as well as the correlation coefficients among physical factors. Then, 1,000 datasets of relevant physical factors were generated according to the calculated averages, standard deviations, and correlations. After that, the 1,000 datasets were used to calculate 1,000 venting volumes. The distribution of these 1,000 venting volumes represented the venting volume at different probabilities. The diagram of probabilistic simulation is shown in Figure 1.

In generating the 1,000 datasets of physical factors, the Cholesky randomization method was used to create a dataset with specified correlation coefficients. First, the physical factors (wave height, ambient air temperature, storage temperature, storage quantity, daily incoming rate, RVP) were transformed to normally distributed data. After that, the correlation matrix was determined (the matrix containing the correlation coefficients among variables-transformed wave height, transformed ambient air temperature, transformed storage temperature, transformed storage quantity, transformed daily incoming rate, and transformed RVP-calculated from the MLR). Then, the Cholesky decomposition process was used to decompose the correlation matrix into a triangular matrix and its transpose, as shown in Equation 5 (Golub and Loan, 1983; Trefethen and Bau, 1997):

$$A = LL^T \quad (5)$$

Where; A is the correlation matrix, L is the lower triangular matrix with real and positive diagonal entries, and L^T is the transpose of L.

After that, a 6 × 1,000 matrix, containing random numbers between 0 and 1, was created (denoted as P). The six columns in matrix P represented the six variables (transformed wave height, transformed ambient air temperature, transformed storage temperature, transformed storage quantity, transformed daily incoming rate, and transformed RVP). Then, a matrix containing the inverse of the standard normal distribution of the elements of the matrix P was generated (denoted as X). After that, matrix X was multiplied by matrix L, as shown in Equation 6. The result was a matrix (denoted as X^*) containing random numbers, the correlation coefficients of which are matrix A:

$$X^* = XL \quad (6)$$

Finally, each column of matrix X^* was multiplied by the standard deviation of each variable (the variable each column represented) and the average of each variable was added to the product (the multiplication result). This process yielded 1,000 sets of random variables, the average, standard deviation, and correlation of which were according to those of the observed values. In the step of calculating venting volumes, 1,000 sets of random variables were used in the MLR to calculate the VOC venting volumes.

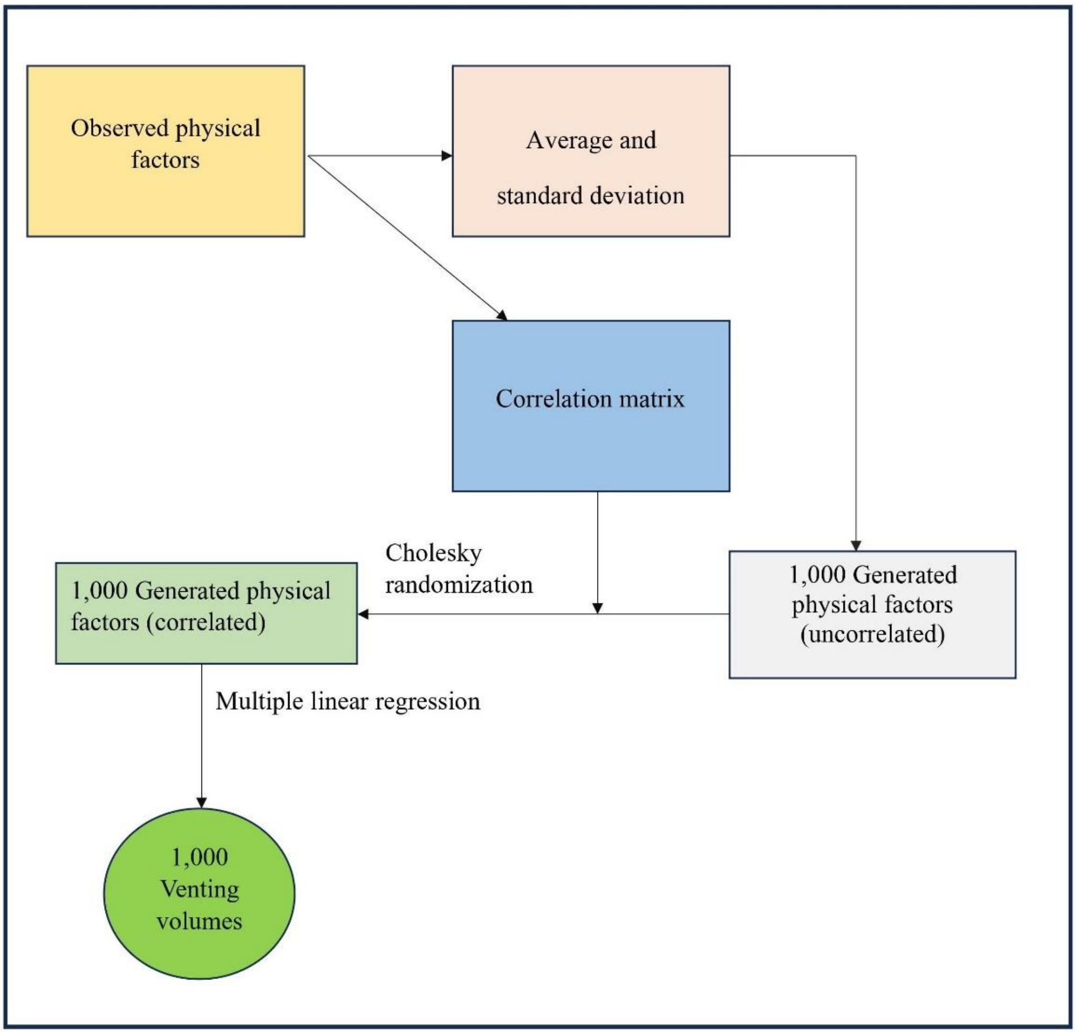

Figure 1. Flowchart of probabilistic simulation

2.4 Evaluation of role of correlation among physical factors

To evaluate the role of correlation among the physical factors, 2 probabilistic simulations were conducted. The first simulation was conducted without correlation among the physical factors. In that simulation, matrix X in section 2.3 was not multiplied by matrix L. The variables were generated by the multiplication of each column of matrix X using the standard deviation of each variable and the addition of the average of each variable to the multiplication result. The second simulation applied correlation among physical factors, which followed all the steps mentioned in section 2.3. The difference between moments (averages, standard deviations, and skewness) and percentiles of the VOC venting volumes from these 2 simulations were used to determine the role of correlation among physical factors.

3. RESULTS AND DISCUSSION

3.1 Data transformation

In the gathered data, there were 40 days for which the VOC venting volumes were less than 90,000 ft^3 due to closure of the vent stack, resulting from poor weather conditions or stack maintenance. Therefore, the data on these 40 days were excluded and only the data on the remaining 326 days were used. The summarized values of physical factors, both before and after the two-step normality transformation, during the study period are shown in Table 1. The ambient air temperature (average of 28.4°C and standard deviation of 0.9°C) was higher and had less variability than those from other studies because the study area was located in the tropical zone (Gjesteland et al., 2019; Hu et al., 2020; Stricklin, 2014). The RVP value had low variability because the NGLs of each batch had a consistent composition. Because of the application of the two-step normality transformation, the transformed data followed a normal distribution. The comparison between the non-transformed and transformed data revealed that the skewness of the transformed data was close to zero.

3.2 Relationship between VOC venting volume and physical factors

The set of terms producing the highest adjusted R^2 of the MLR and the coefficients of these terms, together with the results of the t-test, are shown in

Table 1. Summary of non-transformed and transformed physical factors

Statistic	Wave height		Ambient air temperature		Storage temperature		Storage quantity		RVP		Daily incoming rate	
	Non-transformed	Transformed	Non-transformed	Transformed	Non-transformed	Transformed	Non-transformed	Transformed	Non-transformed	Transformed	Non-transformed	Transformed
Average	1.1 m	1.1 m	28.5°C	28.5°C	29.4°C	29.4°C	492,012 bbls	493,508 bbls	12.1 psi	12.1 psi	43,163 bbls	43,181 bbls
Standard deviation	0.7 m	0.7 m	0.9°C	0.9°C	0.6°C	0.6°C	94,768 bbls	92,919 bbls	0.3 psi	0.3 psi	7,160 bbls	7,142 bbls
Skewness	1.30	-0.05	-0.54	0.10	0.57	0.01	0.33	0.17	0.75	0.33	-0.06	0.00

The abbreviation “bbls” stands for “barrels”.

Table 2. The significant terms were: 1) transformed RVP; 2) transformed wave height; 3) transformed storage temperature; 4) transformed daily incoming rate; 5) transformed RVP × transformed daily incoming rate; 6) transformed RVP × transformed wave height; and 7) transformed RVP^2. Therefore, these sets of terms in the MLR were the best to estimate the VOC venting volume. The significant factors were consistent with those determined using the non-transformed data, as described by Seekramon (2023), except for the addition of the daily incoming rate, which was significant in the current study. The daily incoming rate related to the liquid velocity feeding into the tank. (A high daily incoming rate caused a high velocity and enhanced the turbulence of NGLs, leading to high VOCs venting volume). The other significant factors have been discussed in Seekramon (2023). The significance of the terms 5-7 above (transformed RVP × transformed daily incoming rate, transformed RVP × transformed wave height, and transformed RVP^2) suggested that the effects of RVP, wave height, and daily incoming rate were not constant. For example, a high RVP promoted NGL evaporation, corresponding to the VOC venting volume (Rudd and Hill, 2001; Stricklin, 2014), and at a high daily incoming rate and wave height promoted VOC venting volume (Deligiannis et al., 2016).

Table 2. Terms from MLR between transformed physical factors and VOC venting volume providing highest value of adjusted R^2

Term	Coefficient	Standard error	t- statistic	p-value
Intercept (ft^3)	24,539,128	8,158,959.184	-3.008	0.003
Transformed RVP (psi)	-1,570,508	765,865.167	-2.051	0.041*
Transformed wave height (m)	-681,298.9	328,061.780	-2.077	0.039*
Transformed storage temperature (ºC)	-1,017,555	506,203.820	-2.010	0.045*
Transformed daily incoming rate (bbl)	43.547	20.554	2.119	0.035*
Transformed RVP (psi) × transformed daily incoming rate (bbl)	-3.372	1.696	-1.989	0.048*
Transformed wave height (m) × transformed storage quantity (bbl)	0.064	0.046	1.391	0.165
Transformed storage temperature $(ºC)^2$	16,673.849	8,158.886	1.957	0.051
Transformed RVP (psi) × transformed wave height (m)	69,035.092	17,789.893	3.881	<0.001*
Transformed storage quantity $(bbl)^2$	-9.59×10^{-8}	6.13×10^{-8}	-1.565	0.119
Transformed wave height (m) × transformed ambient temperature (ºC)	5,453.376	3,288.785	-1.658	0.098
Transformed wave height (m) × transformed storage temperature (ºC)	-11,429.679	9,310.032	-1.228	0.221
Transformed RVP $(psi)^2$	68,773.81	31,713.808	2.169	0.031*

* p-value<0.05 (significant); The abbreviation "bbl" stands for "barrel".

The observed and modeled venting volumes are shown in Figure 2. The model produced increases and decreases in the venting volume consistent with the observed values. However, the standard deviation of the modeled data was less than that of the observed data. The MLR had values for R^2 of 0.370, adjusted R^2 of 0.345, and standard error of 54,863 ft^3. The venting volume was high during September-December (days 274-366) because of the influence of the northeast monsoon, which led to an increased wave height. This proved that wave height significantly increased the VOC venting volume.

3.3 Estimation of VOC venting volume based on probabilistic simulation

3.3.1 Cholesky decomposition of correlation matrix

Correlations among the transformed physical factors are shown in Table 3. There were positive correlations between transformed wave height and transformed storage quantity, between transformed wave height and transformed daily incoming rate, between transformed ambient air temperature and transformed storage temperature, between transformed temperature (both ambient and storage temperatures) and transformed RVP, and between transformed storage quantity and transformed daily incoming rate. In addition, there were negative correlations between transformed wave height and transformed temperature (both ambient and storage temperatures), between transformed wave height and transformed RVP, between transformed temperature (both ambient and storage temperatures) and transformed storage quantity, between transformed temperature (both ambient and storage temperatures) and transformed daily incoming rate, between transformed storage quantity and transformed RVP, and between transformed RVP and transformed daily incoming rate.

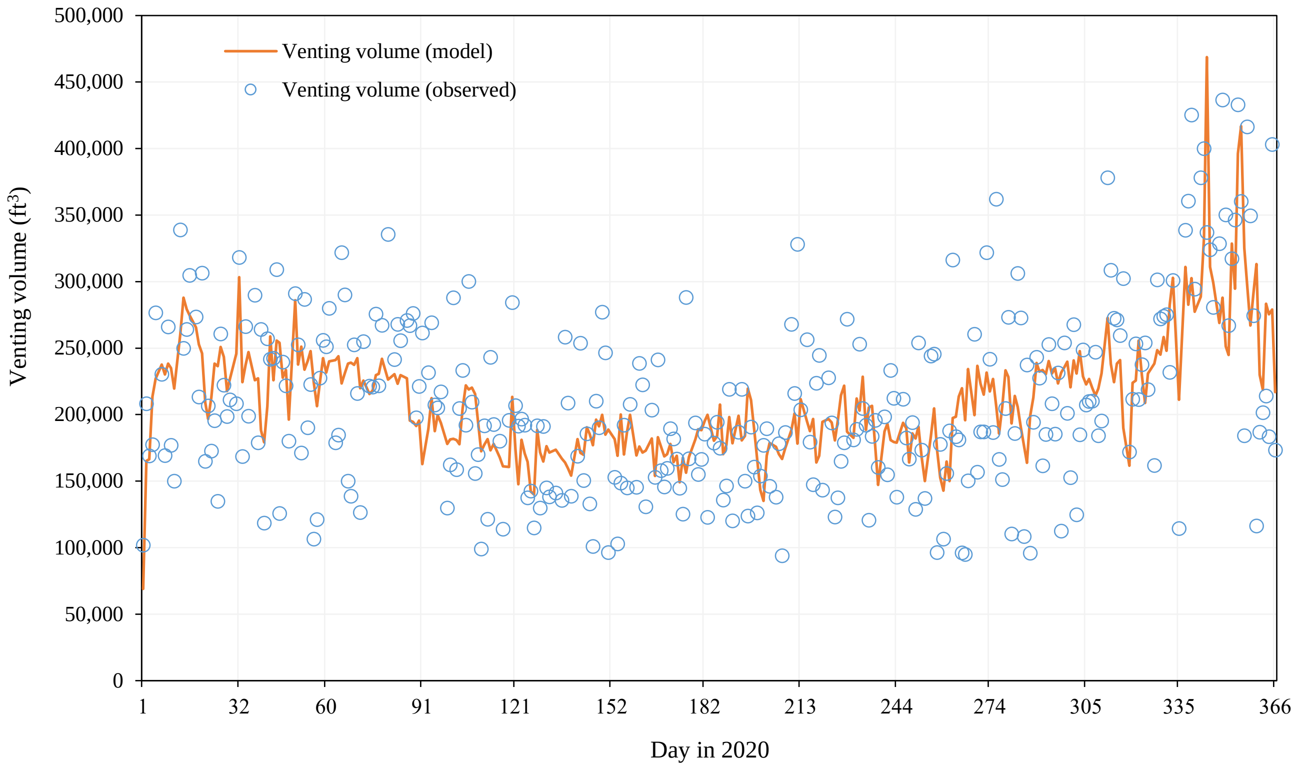

Figure 2. Observed and modeled VOC venting volume from FSO

Table 3. Correlations between each pair of observed transformed physical factors

Transformed wave height	1.000					
Transformed ambient air temperature	-0.326	1.000				
Transformed storage temperature	-0.403	0.592	1.000			
Transformed storage quantity	0.052	-0.116	-0.206	1.000		
Transformed daily incoming rate	0.188	-0.330	-0.194	0.240	1.000	
Transformed RVP	-0.046	0.144	0.189	-0.020	-0.070	1.000
	Transformed wave height	Transformed ambient air temperature	Transformed storage temperature	Transformed storage quantity	Transformed daily incoming rate	Transformed RVP

Based on Table 3, the correlation matrix (A) can be written as shown below:

$$A = \begin{bmatrix} 1.000 & -0.326 & -0.403 & 0.052 & 0.188 & -0.046 \\ -0.326 & 1.000 & 0.592 & -0.116 & -0.330 & 0.144 \\ -0.403 & 0.592 & 1.000 & -0.206 & -0.194 & 0.189 \\ 0.052 & -0.116 & -0.206 & 1.000 & 0.240 & -0.020 \\ 0.188 & -0.330 & -0.194 & 0.240 & 1.000 & -0.070 \\ -0.046 & 0.144 & 0.189 & -0.020 & -0.070 & 1.000 \end{bmatrix}$$

Which yields the result of Cholesky decomposition (L), as shown below:

$$L = \begin{bmatrix} 1.000 & 0.000 & 0.000 & 0.000 & 0.000 & 0.000 \\ -0.326 & 0.945 & 0.000 & 0.000 & 0.000 & 0.000 \\ -0.403 & 0.487 & 0.775 & 0.000 & 0.000 & 0.000 \\ 0.052 & -0.104 & -0.173 & 0.978 & 0.000 & 0.000 \\ 0.188 & -0.284 & 0.026 & 0.210 & 0.916 & 0.000 \\ -0.046 & 0.137 & 0.133 & 0.020 & -0.033 & 0.980 \end{bmatrix}$$

3.3.2 Randomized physical factors

The average, standard deviation, and skewness of the uncorrelated and correlated randomized variables are shown in Table 4. It can be seen that the averages, standard deviations, and skewness were close to those of the observed transformed variables (Table 1).

Tables 5 and 6 show the correlations among randomized variables when the actual correlations among physical factors were and were not applied in the randomization, respectively. When the actual correlations were applied, the correlations among randomized variables (Table 5) were close to those among the observed variables (Table 3). However, when the actual correlations were not applied, the correlations among randomized variables (Table 6) and those among the observed variables differed. Therefore, the Cholesky randomization successfully represented the correlations among physical factors.

3.4 Probabilistic simulation of VOC venting volume

Comparisons between the observed VOC venting volume and the probabilistic simulated VOC venting volumes with and without correlation among physical factors are shown in Table 7. It was found that regardless of whether or not correlations among physical factors were applied, the average simulated venting volumes were close to the observed venting volumes (approximately 210,000 ft^3), and the standard deviations of the simulated venting volumes (approximately 40,000 ft^3) were lower than those for the observed venting volumes (approximately 67,961 ft^3). However, when the correlations were applied, the skewness of the VOC venting volume was more accurate than when the correlations were not applied.

Table 4. Average, standard deviation, and skewness of the correlated and uncorrelated randomized variables

Randomized variable	Transformed wave height		Transformed ambient air temperature		Transformed storage temperature		Transformed storage quantity		Transformed daily incoming rate		Transformed RVP	
	Correlated	Uncorrelated	Correlated	Uncorrelated	Correlated	Uncorrelated	Correlated	Uncorrelated	Correlated	Uncorrelated	Correlated	Uncorrelated
Average	1.1 m	1.1 m	28.5°C	28.5°C	29.4°C	29.4°C	495,266.9 bbls	495,386.4 bbls	43,134.8 bbls	43,071.8 bbls	12.1 psi	12.1 psi
Standard deviation	0.7 m	0.7 m	0.9°C	0.9°C	0.6°C	0.6°C	94,650.3 bbls	94,920.4 bbls	7,041.7 bbls	7,154.8 bbls	0.3 psi	0.3 psi
Skewness	-0.017	-0.017	0.001	0.005	0.016	0.003	0.129	0.136	0.070	0.121	0.030	0.046

The abbreviation “bbls” stands for “barrels”.

Table 5. Correlation between each pair of randomized variables with correlations among physical factors

Transformed wave height	1					
Transformed ambient air temperature	-0.343	1				
Transformed storage temperature	-0.405	0.557	1			
Transformed Storage quantity	0.067	-0.098	-0.196	1		
Transformed daily incoming rate	0.137	-0.309	-0.168	0.228	1	
Transformed RVP	-0.023	0.104	0.139	-0.015	-0.050	1
	Transformed wave height	Transformed Ambient air temperature	Transformed storage temperature	Transformed storage quantity	Transformed daily incoming rate	Transformed RVP

Table 6. Correlation between each pair of randomized variables without correlation among physical factors

Transformed wave height	1					
Transformed ambient air temperature	0.004	1				
Transformed storage temperature	0.013	-0.034	1			
Transformed storage quantity	0.018	0.011	0.004	1		
Transformed daily incoming rate	-0.064	-0.009	-0.014	-0.017	1	
Transformed RVP	0.020	-0.027	-0.032	-0.009	0.009	1
	Transformed wave height	Transformed ambient air temperature	Transformed storage temperature	Transformed storage quantity	Transformed daily incoming rate	Transformed RVP

Table 7. Comparison between observed and probabilistic simulated venting volumes

Statistic	Observed venting volume	Venting volume from probabilistic simulation (correlation applied)	Venting volume from probabilistic simulation (correlation not applied)
Mean (ft^3)	210,984	211,610	210,906
Maximum (ft^3)	436,548	369,461	372,812
Minimum (ft^3)	94,052	120,958	78,711
Standard deviation (ft^3)	67,961	38,828	40,787
Skewness	0.71	0.74	0.51

This finding coincided with other studies that used probabilistic simulation to generate non-normally distributed data (Cao et al., 2013; Headrick and Kowalchuk, 2007; Lin et al., 2022).

The standard deviations of the simulated venting volumes were low because the MLR accounted for only 37.0% of the variability of the venting volume (R^2=0.370). For this reason, the variability of the simulated value was less than that of the observed value (Figure 2). It can be seen in Figure 3 that the simulated venting volumes were accurate at the 54th-63rd percentiles. At lower percentiles, the simulated venting volumes appeared to be higher than the observed venting volumes, while at higher percentiles, the simulated venting volumes appeared to be lower than the observed venting volumes.

The skewness of the simulated VOC venting volume was improved when the correlations among physical factors were applied, because of the natural characteristics of the physical factors that were correlated with each other. Ignoring the correlations among physical factors could result in unrealistic occurrence probability estimates for physical factors, leading to unrealistic skewness. When the correlations were not applied at low percentiles, the simulated venting volumes decreased with decreasing percentile at a higher rate than the observed data. However, when the correlations were applied, the rate of decrease was less, which was more accurate. Therefore, the results of the current study showed that applying correlations among physical factors in the probabilistic simulation of venting volume could improve simulation accuracy by improving the skewness of the simulated VOC venting volume, which was consistent with Batterman et al. (2014). Nevertheless, it should be noted that the observed and simulated venting volumes may not be close to each other when the venting volume is low because days with venting volumes of less than 90,000 ft^3 were excluded from the current study.

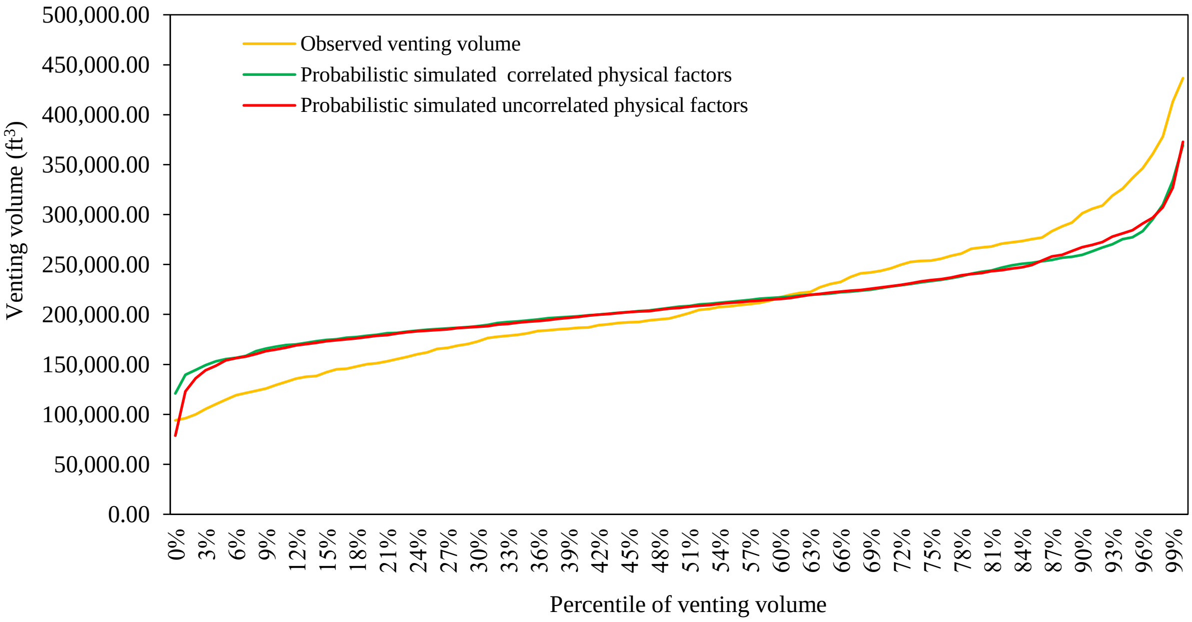

Figure 3. Percentiles of observed and probabilistic simulated venting volumes

4. CONCLUSION

This research highlighted the importance of implementing correlations among physical factors in predicting VOC venting volume emitted from the FSO. Physical factors affecting VOC venting volume, including wave height, ambient temperature, storage temperature, storage quantity, RVP, and daily incoming rate, were transformed to normally distributed data. Second-order MLR with interaction effects was used to determine the relationship between the transformed physical factors and the VOC venting volume. The selection of terms (transformed physical factors and interaction effects) in the MLR was based on maximizing the adjusted R^2, with the significance of each term being tested using a t-test. The significant terms for the prediction of VOC venting volume were: 1) transformed RVP; 2) transformed wave height; 3) transformed storage temperature; 4) transformed daily incoming rate; 5) transformed RVP × transformed daily incoming rate; 6) transformed RVP × transformed wave height; and 7) transformed RVP^2. The MLR had values for R^2 of 0.370, for adjusted R^2 of 0.345, and for standard error of 54,863 ft^3. Then, probabilistic simulation was applied to generate 1,000 sets of probable physical factors in 2 scenarios (implementing and not implementing the correlations among physical factors). The generated physical factors were used to estimate 1,000 VOC venting volumes. The averages of the estimated VOC venting volumes corresponded to the observed data for all scenarios. However, the standard deviations of the estimated VOC venting volumes were low because of the low goodness of fit of the MLR. Nevertheless, the skewness of the simulated VOC venting volume was improved when the correlations among physical factors were applied. Therefore, the implementation of correlations among physical factors provided better simulation results. This improvement should benefit many works using probabilistic simulation, such as benefit-risk assessment.

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