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Improving the Performance of the Acoustic Emission Method in the Condition Monitoring Process by Optimizing the Placement of Sensors in Oil Refinery Tanks

Hamzah Ali Alkhazaleh [1]*, Rebeya Anzum [2]

[1] College of Engineering and IT, University of Dubai, Academic City, 14143, Dubai, UAE
[2] Postgraduate Student, Kulliyyah (faculty) of Engineering, International Islamic University Malaysia, (IIUM). P.O. Box 10, 50728 Kuala Lumpur, Malaysia

Abstract

In maintenance, state or condition monitoring, the set of actions describes the state of the machine and its changes over time, based on parameters such as vibrations, sound, performance, lubrication, and temperature. Monitoring the condition of a system requires an optimal network of different sensors to prevent faults occurring in each of the components at an early stage and prevent more severe failures. One of the new methods for monitoring the status is acoustic emission method, which is developed in this paper. The main objective of the present work is to optimize the position of the sensors in monitoring the situation with the method of acoustic emission. The maximum determinant of FISHER Information Matrix (FIM) is the optimal position of the sensors. For this purpose the genetic algorithm is used to find the maximum determinant of Fisher's data matrix for optimal sensor positioning. A case study was conducted on one of the storage tanks of refinery. The design parameters for the positioning of the sensors are respectively the angles relative to the reservoir source and the sensor height relative to the reservoir surface. Finally, the optimal positioning of the sensors is based on the proposed algorithm.

Keywords: Condition monitoring, Acoustic emission, FISHER Information Matrix, Genetic algorithm

1. Introduction

Stochastic optimization algorithms for wireless sensor network location consider all the problem solving space in the case study, that is, they simultaneously search for a solution to optimize the objective function in the space of unknowns. One of the prominent features of these algorithms is their randomness based on an evolutionary process (Sikorski, 2019; Sikorski, 2018; AlShorman et al., 2021).

***Corresponding author:** Hamzah Ali Alkhazaleh, College of Engineering and IT, University of Dubai, Academic City, 14143, Dubai, UAE, E-mail: halkhazaleh@ud.ac.ae

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In all these algorithms, it is necessary to calculate sensor coverage in the network as an objective function. In fact, the improvement of the coverage is done according to how the coverage is calculated. In Cyrille (2012) investigated the effect of redundancy in sensor network optimization based on the Fisher matrix. Based on the analysis done in this research, the sensor that is in node 1 and another sensor that is in node 2 and in the vicinity of node 1 receive the same information. However, in the Fisher matrix optimization method, the two mentioned nodes have the same effective independence coefficient values. In this research, different components of the system are studied separately and the whole system is not studied at once. In this method, first, the finite element model of a component in a model is developed, and subsequent operations are applied to the nodes of these elements. The output of this method is the best geometric location for a certain number of sensors. For example, if only 3 sensors are available based on economic limitations, the best place for those sensors is determined from the point of view of the amount of information received. The topic of information redundancy is an effective factor in determining the optimal location. But adding this factor in calculations increases their complexity. Most of the other works done in this field have focused on applying this method to different components. Al-Khadaf et al (2012) optimized the position of sensors in a condition monitoring system for a gearbox. In this work, a new program of the initial optimization method for the position of the sensors and adjusting the signal conditions in the gearbox system using vibration sensors and sound propagation has been investigated. In this research, only laboratory studies have been done and no numerical analysis has been done.

Duff et al., (2012) have studied the acoustic source positions in a two-dimensional plane. This position is according to the Time Difference of Arrival and based on the arrangement of three arbitrary sensors on the surface of the two-dimensional plane. In order to estimate the available deviations, the exact analysis method of Kramer-Raw boundaries was used and a comparison was made with the Monte Carlo method. Thomas et al. (2013) optimized the position of the sensor for an underwater structure using the sound propagation test method. In particular, they focus on the test set and obtain the location of the source by measuring the range between the underwater source and a number of sensors using GPS. This article aims to investigate the main theoretical challenges and begins with the review of previous work in the region. By using appropriate mathematical relationships, they have well defined the method of maximizing the determinants of the FIM. Also, they have obtained the minimum variance of position estimation error by Kramer's method. For further explanation, the details of Monte Carlo simulation in 2D and 3D space with selected position algorithm are presented to confirm the numerical results.

Randolph et al. (2015) presented the algorithms of sensor network independence. Considering that there are no "anchor" nodes with known locations. Therefore, to estimate the time of arrival and the direction of arrival between sources and sensors, source signals on the surface have been used for unknown locations. These measurements are used to calculate maximum likelihood relative calibration solutions where the nodes are centered relative to each other. Then, the information related to the previous positions of the sensors, in the form of irregular strengths, is used to obtain the maximum estimates of the location and direction of the sensors. Analytical statistical performance ranges have been obtained for two estimates and examples have been presented that show the performance of the algorithms. In Ono (2019) optimized the replacement of the sensor network based on risk to improve the condition monitoring process on the steam turbine sensor network. According to the importance of sensor placement in the situation monitoring process, they have provided an algorithm for optimal positioning of sensors. The algorithm includes two criteria. The first criterion is the uncertainty of the information obtained from the sensors and it is determined based on the uncertainty of predictions about sensor failures. The second criterion is the sensor failure risk and is determined based on the reliability of the sensors and the accuracy of the information obtained from the sensors. They proved that the results obtained from two criteria are not necessarily similar and in some cases they are completely different from each other. In the case of studies for steam turbines, they proved that the values related to the uncertainty index are close to each other, but in the risk criterion, these values are significantly different from each other. For this reason, the criterion of uncertainty will be decisive.

Pakianater et al. (2018) conducted a study on the number of acoustic emission sensors to detect surface fractures and use the bees algorithm. This method is based on confrontation to optimize the number of sensors needed to detect surface fractures. This article describes the method used in this study in which surface dimensions are specified by the user. The results show that in theory and through simulation, the bees algorithm is able to determine the minimum number of sensors required to determine the surface fracture with acceptable accuracy. The described method can be used for optimization in other engineering structures. As can be seen, the optimization of sensor placement in the acoustic emission method using an optimization algorithm has been less investigated. For this reason, in the present research, an attempt will be made to determine suitable places for replacing sensors by presenting a comprehensive optimization algorithm.

In the present work, the optimization of the location of the source and sensors for monitoring the condition of the storage reservoirs with the acoustic emission method has been done by the genetic algorithm optimization. In the second section, the materials and methods used for acoustic emission, the extraction of Fisher's information matrix equations and the genetic algorithm have been discussed and investigated. In the third section, a case study was conducted for storage tanks in Refinery, and for the tank, the optimal location of sensors and source was extracted by genetic algorithm. In the last section, conclusion and discussion, advantages and disadvantages of this method have been discussed.

2 Method

Acoustic emission is a constantly evolving field and currently the focus of research-based and applied studies in this field. Acoustic emission testing is a new and advanced method in the field of non-destructive testing. This method has been expanded in a wide range of NDT applications, such as inspection of metal pressure vessels, piping systems, reactors, etc., and this method can be used to detect and locate various defects in structures under load and components. they used the acoustic emission test is a passive technique that analyzes the ultrasonic pulses emitted by different sources inside the material at the moment of its occurrence, and its main difference with methods such as ultrasound or radiography is the same. Figure 1-2 is an overview of status monitoring by Acoustic emission method. Figure 2-2 shows the placement of sensors and the signals emitted from the sensors around a crack. The forces applied to the part cause it to be stimulated and create various tensions. These tensions create sources that emit ultrasonic waves.

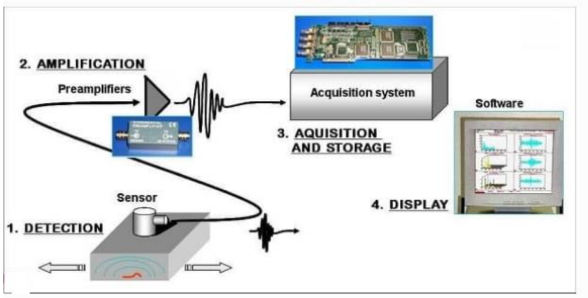

Figure 1: status monitoring by acoustic emission method

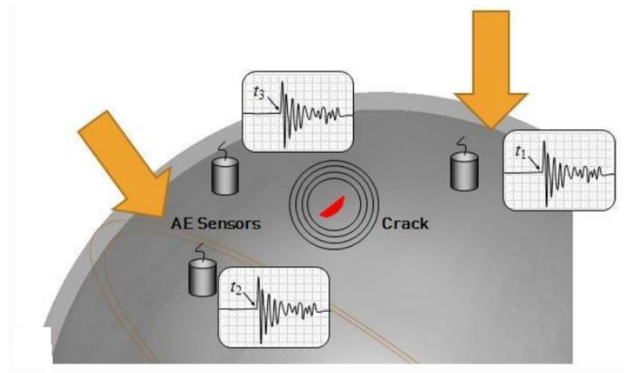

Figure 2: Position of sensors and signals emitted from sensors in acoustic emission

2.1 Governing equations to optimize the positioning of sensors

The optimization of source and sensor position has been the interest of many researchers in recent years. Estimating the optimal position of the source based on the optimal arrangement of sensors is a challenging issue that should be considered. Source location optimization can be defined as using a set of sensors to estimate the exact location of a source based on distinct details or information related to the relative position of the sensors to the source. There are different algorithms to optimize the position of the sensors, which is used in the present work from the ratio of the received signal strength (RSS) by the sensor. The RSS approach involves sending a signal with a known power and using the received signal power and the loss coefficient to estimate the distance between the source and the sensor. Equation 1 shows the signal strength (Li et al., 2022).

$$s = \frac{A}{d^{\beta}}$$ (١)

In the above equation, s is the received signal strength ratio, A is the source signal strength, β is the path loss coefficient, and d is the distance between the sensor and the source, it can be as:

$$\log(s_i) = \log(A) - \beta * \log(d_i)$$ (٢)

In the above equation, d is introduced as equation 3.

$$d_i = x_i - y \quad (3)$$

In the above equation, x indicates the position of the sensors, index i indicates the number of sensors, and y indicates the position of the source.

2.2 Fisher information matrix

For the first time, an organized method in the field of sensor placement optimization was carried out on space equipment (Xu et al., 2021). The basis of this method is based on maximizing the determinant of Fisher's information matrix. Fisher's information in statistical mathematics is a way to measure the information that the observable random variable x contains about an unknown parameter θ. In fact, Fisher's information represents the variance of the results or the expected value of the observed information. According to the mentioned definitions, this concept can be used to measure the value of information obtained from sensors at different points. In this method, the entire structure is first extracted using finite element methods, meshed and information matrix for different nodes. Then, by using an optimization method, the nodes that obtain the maximum determinant of Fisher's information matrix are selected as the suitable places for replacing the sensors. Since the validation of sound emission for reservoirs with numerical methods and laboratory results is expensive, therefore, based on the method used in this article, we assume that the maximum determinant of the Fisher information matrix is the optimal position of the sensors. Referring to the source (Zeng, 2021), Fisher's information matrix is extracted as follows. By defining L as equation 4, we have:

$$\mathrm{L} = [\log \mathrm{s}_1, \ldots.. \log \mathrm{s}_\mathrm{i}]^\mathrm{T} \tag{4}$$

The density probability function is defined as equation 5.

$$P_{s-y} = \frac{1}{(2\pi)^{\frac{n}{2}} * \sigma^n} \exp\left\{\left(-\frac{1}{2}\right) * \left(\frac{\|L - Z\|}{\sigma^2}\right)\right\} \tag{5}$$

In the above equation, Z is defined as equation 6.

$$\mathrm{Z} = [\log \mathrm{A} - \beta \log(x_1 - y), \ldots.. logA - \beta \log(x_n - y)]^T \tag{6}$$

So:

$$X = \frac{\partial}{\partial y} \ln(P_{s-y})\,(s - y) \tag{٧}$$

$$X = -\left[\frac{\partial z}{\partial y}\right]\left(\frac{L - Z}{\sigma^2}\right) = -\frac{1}{\sigma^2}\left(\frac{\partial Z^T}{\partial y}\right) W \tag{٨}$$

$$W = [w_1, w_2, \ldots. w_n]$$

$$z_i = logA - \beta log|x_i - y|$$

$$\frac{\partial z_i}{\partial \mathrm{y}} = \left(-\frac{\beta}{2}\right)\frac{\partial}{\partial y} log|x_i - y|^2 = -\frac{\beta}{ln10}\left(\frac{x_i - y}{|x_i - y|^2}\right) \tag{9}$$

$$U = \left[\frac{x_i - y}{|x_1 - y|^2}, \ldots. \frac{x_i - y}{|x_n - y|}\right] \tag{10}$$

$$X = \frac{\beta}{\sigma^2 ln10} UW \tag{11}$$

Fisher's information matrix according to the source (Michael et al., 2018) is defined as equation 12.

$$FIM = E[XX^T] = \frac{\beta^2}{\sigma^2 ln10^2} UU^T \tag{12}$$

From the source [28] it can be concluded that

$$FIM = [Z * Z^T] \tag{13}$$

The Fisher information matrix was extracted based on the signal strength, now according to the theory in source (Stella-Rita, 2010), the maximum determinant of the Fisher information matrix is the best position for the sensors.

2.3 Working method based on Fisher's information matrix

Meshing of the studied equipment

In the present work, the optimization of the position of the sensors for a storage tank in the refinery has been investigated. The way of meshing this tank is as shown in Figure 1.

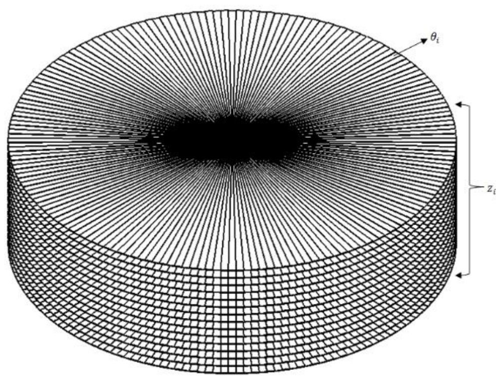

Figure 1: How to mesh the tank

As can be seen in Figure 1, first we have meshed the height, then we have angled the surface at each height and applied it in the Fisher information matrix. Each of these nodes is a sensor position. Equation 14 shows the components of the z matrix at each height.

$$\begin{aligned} Z &= \begin{bmatrix} logA - \beta \log(Rcos\theta_i - y) \\ logA - \beta\log\,(Rsin\theta_i - y) \end{bmatrix} \\ Z^T &= [logA - \beta \log(Rcos\theta_i - y) \quad logA - \beta\log\,(Rsin\theta_i - y)] \end{aligned} \tag{۱۴}$$

In the above equation, R is the radius of the tank. Now, Equation 15 presents Fisher's information matrix, which is considered as the objective function.

$$FIM_i = \begin{bmatrix} logA - \beta \log(Rcos\theta_i - y_x) * logA - \beta \log(Rcos\theta_i - y_X) & logA - \beta \log(Rcos\theta_i - y_x) * logA - \beta\log\,(Rsin\theta_i - \\ logA - \beta \log\left(Rsin\theta_i - y_y\right) * logA - \beta \log(Rcos\theta_i - y_x) & logA - \beta \log\left(Rsin\theta_i - y_y\right) * logA - \beta\log\,(Rsin\theta_i - \end{bmatrix}$$

(15)

The way to calculate the position of the source is that for any arbitrary radius and angle that is placed on the bottom of the tank, we find the components along the coordinate axes and place them in the Fisher information matrix. Equation 16 shows the components of y.

$$
\begin{aligned}
y_x &= R_2 COS\theta_2 \\
y_y &= R_2 SIN\theta_2
\end{aligned}
\tag{16}
$$

In the above equation, R_2 is the radius of the source on the bottom of the tank and θ_2 is the angle of the source on the bottom of the tank. Now that the objective function is known, we will examine the genetic algorithm to maximize the determinants of the Fisher information matrix.

2.4 Problem solving algorithm

The goal is to optimize the position of the sensors by maximizing the determinant of the Fisher information matrix with the help of genetic algorithm. On the other hand, using the Monte Carlo method, the best area for the location of the source has also been checked. First, we examine the Monte Carlo method in finding the suitable area for the source.

2.5 Monte Carlo method

Using the Monte Carlo method to find the optimum source area is to divide the reservoir surface into 8 equal areas and randomly distribute a number of source positions on this surface, then for each source using the genetic algorithm for the maximizing the determinant of the Fisher information matrix, we get the optimal position of the sensors. Now, according to the optimal position of the sensors, the area that has the largest number of answers is the suitable area for the placement of the source. Figure 2 is the Monte Carlo algorithm for finding the appropriate source placement area.

2.6 Optimal location of sensors using genetic algorithm

Now, the appropriate area for the location of the source is obtained. With the location of the source being known, the optimal position of the sensors is obtained by maximizing the determinant of Fisher's information matrix with the help of genetic algorithm. Figure 3 shows the general process of the solution algorithm.

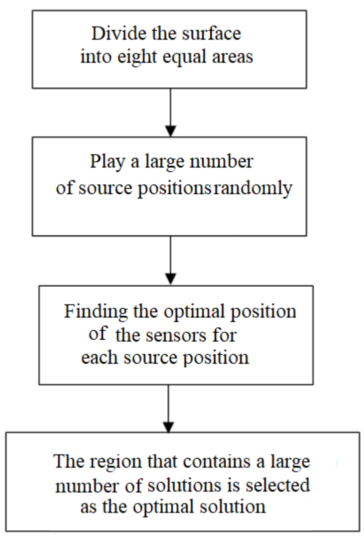

Figure 2: Monte Carlo algorithm to find suitable source area

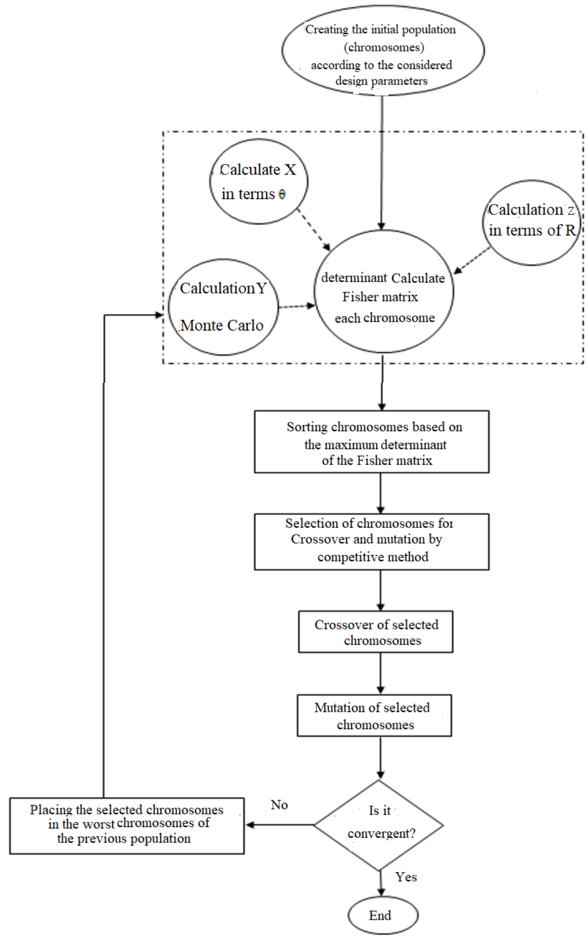

Figure 3: General problem solving algorithm

3. Results

Monitoring the condition of storage tanks in Refinery is one of the most essential possible tasks because these tanks store a large amount of petroleum products in themselves, therefore the smallest defect or failure of these tanks will cause irreparable damage to the oil industry. It creates the country. In the present work, we are going to investigate one of the storage tanks in the refinery to monitor the situation using the acoustic emission method and obtain the optimal position of the sensors for the acoustic emission method.

Case Study: A reservoir in Refinery, whose specifications are in accordance with Table 1, is considered, and a source and three sensors are considered for acoustic emission. The type of sensors used for sound emission testing in Refinery is Kistler type 8152A (Bejger and Drzewieniecki, 2019). The aim is to optimize the location of the sensors and the source with the aim of maximizing the Fisher information matrix based on the strength of the signal sent from the source. In order to maximize the determinant of the Fisher information matrix, which is a function of the signal strength, a well-known genetic algorithm with an objective function has been used. Genetic algorithm is a very powerful tool for optimization with random method and is used in many fields of optimization. Table 2 presents the input parameters of the problem. Also, Table 3 shows the design parameters and their ranges.

Table 1: Specifications of the investigated tank in the refinery

Tank item no	TT-2001
Capacity	34.617 m^3
Service	Crude oil
Material	ASTM A283 Gr.c

Table 2: Input parameters of the problem

Input parameters	Value
BETA for mode with reservoir fluid	۲۰
Signal strength	۱۰۰۰
The number of populations for each iteration of the genetic algorithm P	۹۰۰

Table 3: Range of design parameters

Range	Range
Sensor position angle relative to the origin of coordinates θ	$0 < \theta < 360$
The height of the sensor placement relative to the origin of Z coordinates	$0 < Z < 18$

3.1 Find the right area for the resource

Table 4 shows the zoning areas for the location of the source. Also, Figure 2-3 shows the way of zoning in the storage tank for the source location.

Table 4: Zoning for optimal source location

Zone	The position of the placement angle relative to the coordinate origin
Zone 1	$0° < \theta_y < 45°$
Zone2	$45° < \theta_y < 90°$
Zone3	$90° < \theta_y < 135°$
Zone4	$135° < \theta_y < 180°$
Zone5	$180° < \theta_y < 225°$
Zone6	$225° < \theta_y < 270°$
Zone7	$270° < \theta_y < 315°$
Zone8	$315° < \theta_y < 360°$

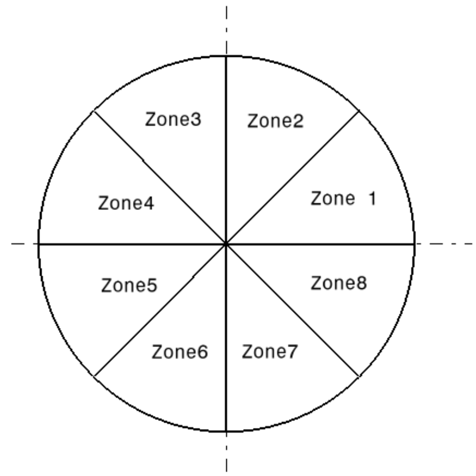

Figure 4: Zoning to find the optimal position of the source

As shown in figure 5, 100 different positions are considered for the source and using the genetic algorithm, the distribution of the optimal position of the sensors is extracted and by using this distribution, the optimal location of the source can be determined. Figure 5 shows the sensor distribution according to the angle of placement of the source on the tank. The source placement angle for this chart is between 0 and 45 degrees. As it is clear in the diagram, the number of 15 optimal sensor positions out of 100 optimal positions is located in this area. Figure 6 shows the sensor distribution according to the angle of placement of the source on the tank. The source placement angle for this chart is between 45 and 90 degrees. As it is clear in the diagram, the number of 30 optimal sensor positions out of 100 optimal positions is located in this area.

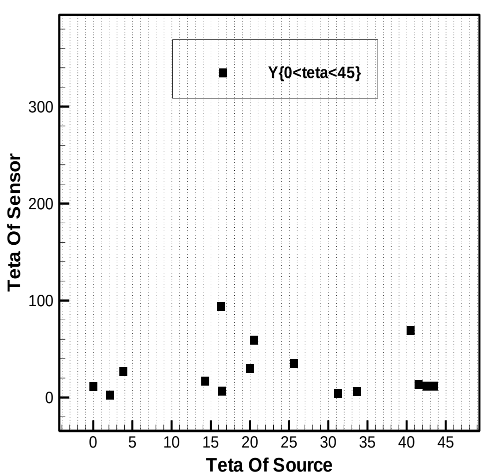

Figure 5: Optimal sensor position distribution for the first source area

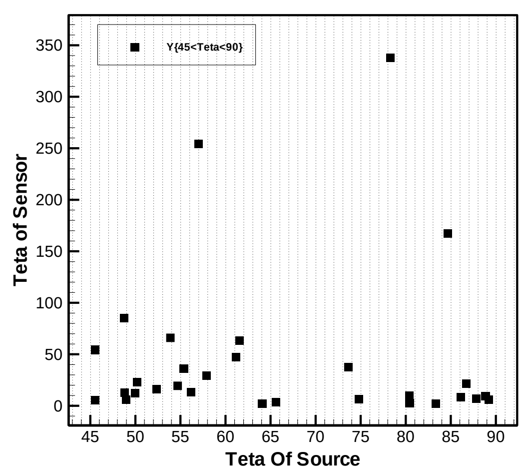

Figure 6: Optimal sensor position distribution for the second source area

Figure 7 shows the sensor distribution according to the angle of placement of the source on the tank. The placement angle of the source for this diagram is between 90 and 135 degrees. As shown in the diagram, the number of 10 optimal sensor positions out of 100 optimal positions is located in this area. Figure 8 shows the sensor distribution according to the angle of placement of the source on the tank.

The source placement angle for this chart is between 135 and 180 degrees. As shown in the diagram, the number of 10 optimal sensor positions out of 100 optimal positions is located in this area.

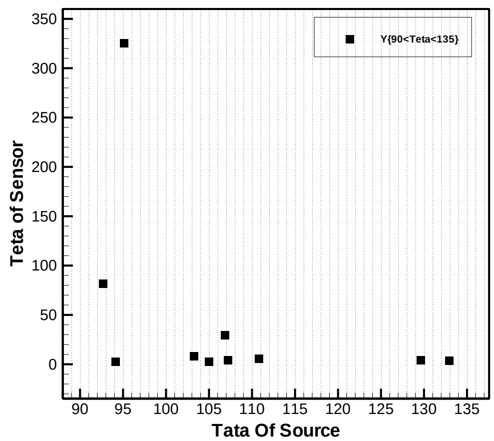

Figure 7: Distribution of the optimal position of the sensor for the third source area

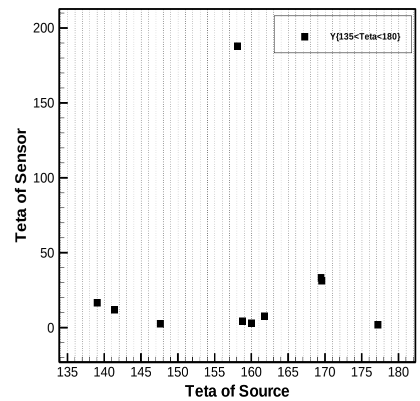

Figure 8: Distribution of the optimal sensor position for the fourth source area

Figure 9 shows the sensor distribution according to the angle of placement of the source on the tank. The angle of placement of the source for this diagram is between 180 and 225 degrees. As shown in the diagram, 8 optimal sensor positions out of 100 optimal positions are located in this area. Figure 10 shows the sensor distribution according to the angle of placement of the source on the tank. The angle of placement of the source for this diagram is between 225 and 270 degrees. As shown in the diagram, the number of 10 optimal sensor positions out of 100 optimal positions is located in this area.

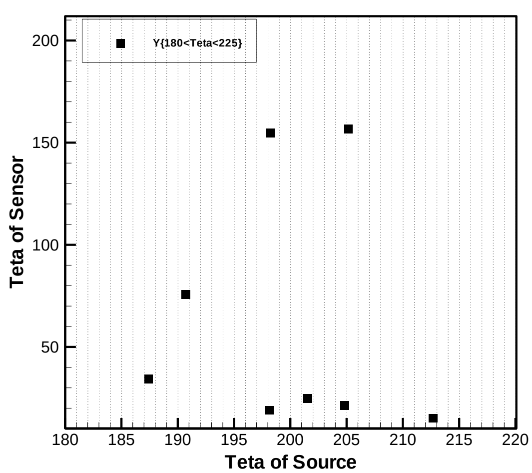

Figure 9: Distribution of the optimal sensor position for the fifth source area

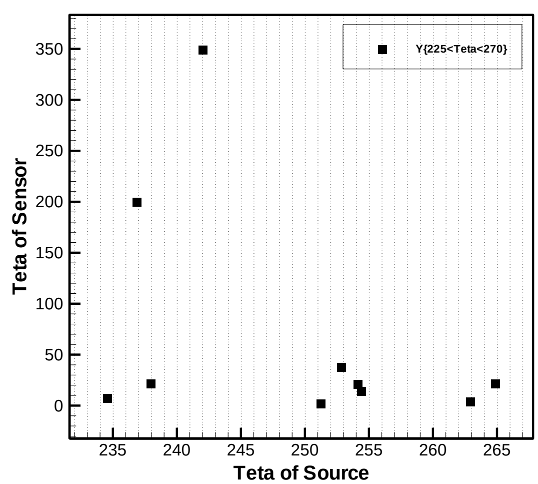

Figure 10: Optimal sensor position distribution for the sixth source area

Figure 11 shows the sensor distribution according to the angle of placement of the source on the tank. The source placement angle for this chart is between 270 and 315 degrees. As shown in the diagram, the number of 5 optimal sensor positions out of 100 optimal positions is located in this area.

Figure 12 shows the sensor distribution according to the angle of placement of the source on the tank. The source placement angle for this chart is between 315 and 360 degrees. As shown in the diagram, the number of 5 optimal sensor positions out of 100 optimal positions is located in this area.

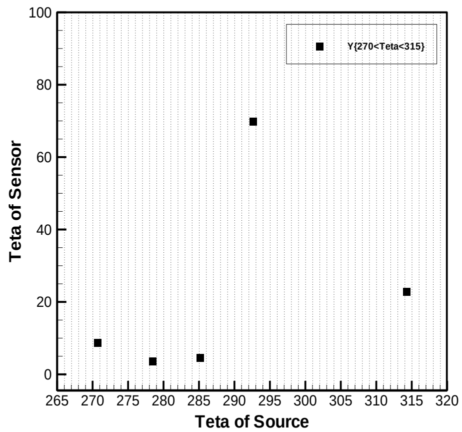

Figure 11: Distribution of the optimal sensor position for the seventh source area

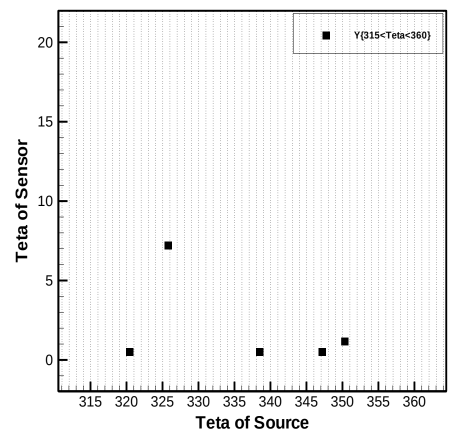

Figure 12: Optimal sensor position distribution for the eighth source area

Figure 13 shows all the location of the source. As it is clear from the diagram, the distribution of each sensor is higher for the source position of the second area, so according to the Monte Carlo method, the best source position in the second area is the angle between 45 degrees and 90 degrees. It is necessary to explain that this distribution of sensors is the optimal value extracted from the genetic algorithm. Now that we know the best location of the source, we go to the best position of the sensors using the genetic algorithm.

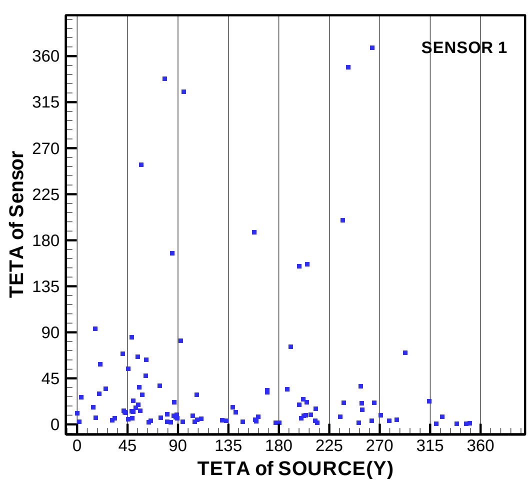

Figure 13: Sensor distribution diagram according to the position of different sources

3.2 Optimizing the position of sensors using genetic algorithm

We run the code for three different source positions, both the radius and the angle of which are randomly selected in the second area, and we find the optimal position of the sensor for each source and compare them. The table 5 shows the location of sources in the second area.

Table 5: Location of the source in the second area

Source	Angle relative to the coordinate origin	Radius
First	50 degree	9m
Second	65 degree	17m
Third	83 degree	25m

3.3 Optimizing the position of sensors using genetic algorithm for different source positions

The convergence process of the genetic algorithm for the first source is shown in Figure 14. It is necessary to explain that the condition of genetic algorithm convergence is that after a certain number of repetitions, the algorithm can no longer maximize the value of the determinant of Fisher's information matrix, so the process continues in the form of a constant line, in which case it can be concluded that the algorithm has converged. Table 6 shows the optimal position of the sensor for the first source mode.

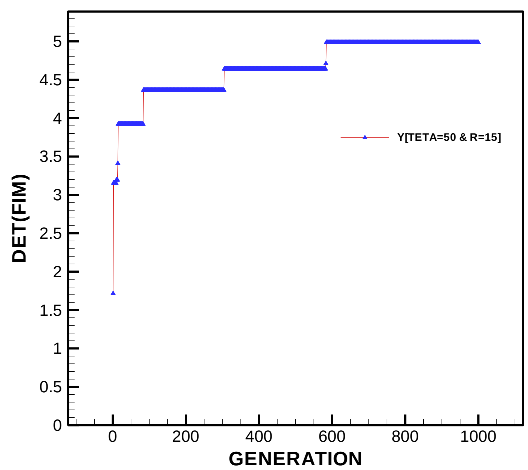

Figure 14: The convergence process of the genetic algorithm to find the maximum determinant of the Fisher matrix

The distribution of design parameters in the process of genetic algorithm convergence are shown in Figures 15 and 16. As can be seen from the graphs, the height distribution is mostly between 0 and 2 meters and the angle is between 0.5 and 45 degrees.

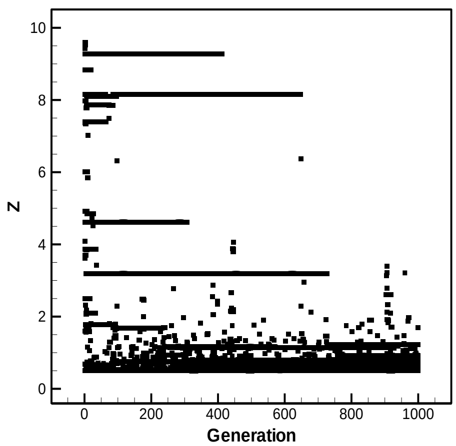

Figure 15: Sensor height parameter distribution in the convergence process

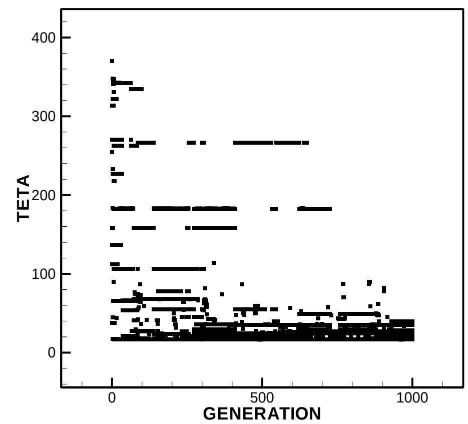

Figure 16: Sensor angle parameter distribution in the convergence process

Table 6: Optimal values for sensors in the first source position

Sensor	Determinant value of the Fisher information matrix	Angle relative to the coordinate origin	Height from the bottom of the tank
First	۵/۳۳۴۸۰۷	۱۲/۱۵۴۷۱	۰/۷۹۷۲۲۳۲
Second	۴/۶۹۸۴۶۶	۲/۳۱۲۳۷۷	۲/۹۰۶۲۴۶
Third	۴/۳۰۱۵۸۹۵	۳/۹۶۷۵۹۱	۲/۹۰۲۵۵۵

The process of convergence by genetic algorithm to find the maximum determinant of the Fisher information matrix for the position of the second source is shown in Figure 17. Table 7 presents the optimal values obtained by the genetic algorithm.

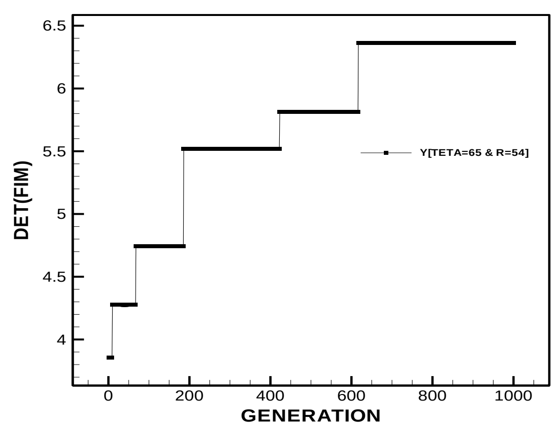

Figure 17: The convergence process of the genetic algorithm to find the maximum determinant of the Fisher matrix

The distribution of design parameters in the process of genetic algorithm convergence are shown in Figures 18 and 19. As can be seen from the graphs, the height distribution is mostly between 0 and 2 meters and the angle is between 0.5 and 45 degrees.

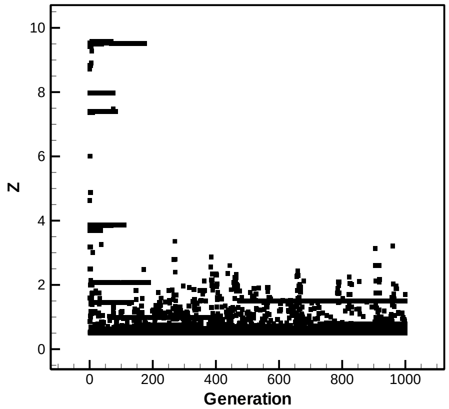

Figure 18: Sensor height parameter distribution in the convergence process

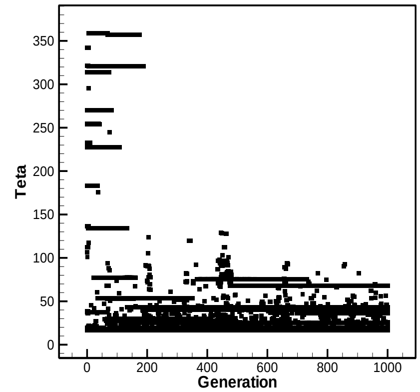

Figure 19: Sensor angle parameter distribution in the convergence process

Table 7: Optimal values for the sensors in the second source position

Sensor	Determinant value of the Fisher information matrix	Angle relative to the coordinate origin	Height from the bottom of the tank
First	۶/۴۴۴۱۰۵	۱۱/۳۰۰۶۵	۰/۵۰۱۱۸۶۷
Second	۵/۸۹۸۴۵۴	۳/۰۶۰۹۸۶	۲/۵۰۰۰۰۰۰
Third	۵/۵۵۱۵۷۴۱	۴۱/۴۶۰۹۱	۲/۸۶۱۳۰۰

The process of convergence by genetic algorithm to find the maximum determinant of the Fisher information matrix for the position of the third source is shown in Figure 20. Table 8 presents the optimal values obtained by the genetic algorithm.

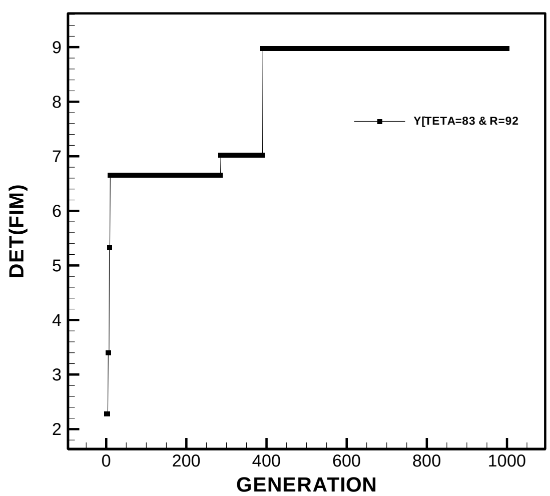

Figure 20: The convergence process of the genetic algorithm to find the maximum determinant of the Fisher matrix

Table 8: Optimum values for the sensors in the position of the third source

Sensor	Determinant value of the Fisher information matrix	Angle relative to the coordinate origin	Height from the bottom of the tank
First	۹/۰۱۵۴۸	۶۶/۱۳۶۵۲	۰/۸۸۴۷۵۰۱
Second	۷/۰۳۷۴۹۰	۳/۵۲۱۴۰۸	۲/۵۰۰۱۸۳
Third	۶/۷۱۲۳۴۵۶	۸۹/۴۱۱۴	۷/۵۹۵۵۲۰

As it is clear from the results, as the source position approaches the tank wall, the determinant of Fisher's information matrix moves to a larger number. Also, in the figures below, the distribution of sensors to reach the optimal state for the position of the third source is shown in Figure 21 for the angle distribution and Figure 22 for the height distribution. As can be seen from the graphs, the height distribution is mostly between 0 and 2 meters and the angle is between 0.5 and 45 degrees.

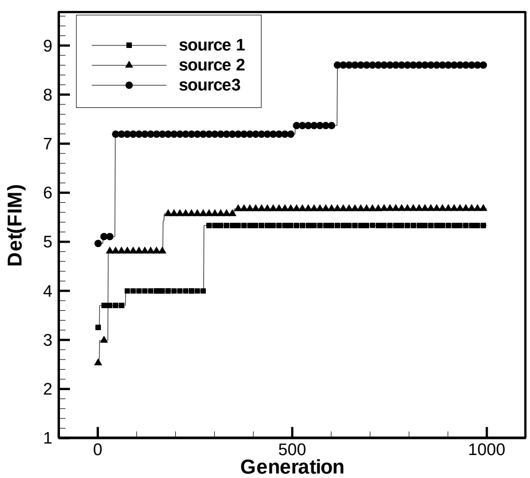

Figure 21: Comparison of the convergence process for three different source positions

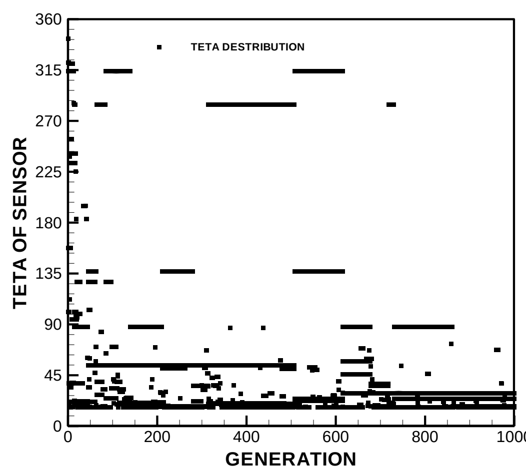

Figure 22: Angle distribution of sensors to find the optimal value

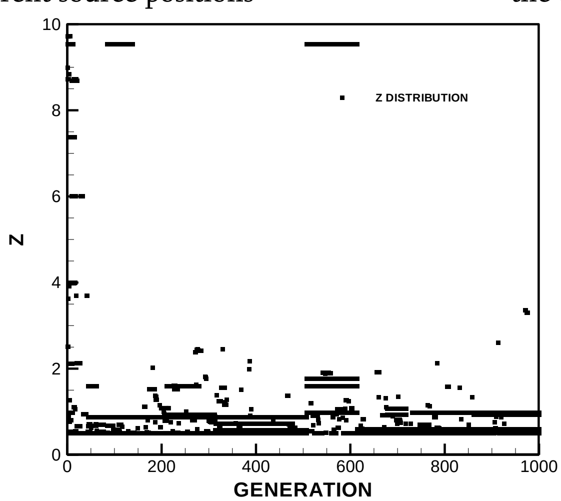

Figure 23: Height distribution to find the optimal value

4. Conclusion

In the present work, we optimized the position of the sensors to perform the acoustic emission process to monitor the condition of the storage tank in Refinery. We also used the Monte Carlo method to find the suitable area for the location of the source and proved that the second area is the best location for the source. Genetic Algorithm is a powerful tool to find the optimal position of the sensors and provides the exact position of the sensors. Based on the results of the present work, it is possible to easily find the optimal position of the sensors for monitoring the condition of the reservoirs without cost. In the present work, using the Monte Carlo location method, the best area for the placement of the source for the sound emission test was presented. By dividing the tank surface into eight areas, the second area was the area where the optimal position of the sensors had more answers than the other areas. After finding the suitable area for the source location (second area), three random positions were considered for the source in the second area, and using the genetic algorithm, the determinant of the Fisher information matrix was maximized, and the optimal position of the sensors was obtained based on the maximum value of the determinant. In the process of maximizing the genetic algorithm, the distribution of the parameters that the algorithm produced is presented. Also, a comparison of the convergence process of the genetic algorithm was shown for three source positions. From this diagram, it can be concluded that each position value of the source radius is closer to the reservoir radius. The genetic algorithm determines the value of the matrix. It gives more information than other source positions, which is reasonable considering the proximity of the source to the sensor. The things that can be done in line with the current research are as follows:

- Optimizing the position of the sensors can be done with other optimization algorithms.
- It is also possible to research the optimization of the number of sensors.
- Instead of using the optimization algorithm method, the effective coefficient method can also be used.
- These methods can be implemented for other structures as well.
- It is possible to solve the problem by considering the signal-to-noise ratio.

References

1. Alain Le Duff, Seif Eddine Hamdi, Guy Plantier, Anthony Sourice, Romain Feron, Cramer-Rao bounds for acoustic emission events localization in a flat plate, Société Française d'Acoustique, 2012, hal- 00810842.
2. AlShorman, O., Alkahatni, F., Masadeh, M., Irfan, M., Glowacz, A., Althobiani, F., ... & Glowacz, W. (2021). Sounds and acoustic emission-based early fault diagnosis of induction motor: A review study. *Advances in Mechanical Engineering*, *13*(2), 1687814021996915.
3. Bejger, A., & Drzewieniecki, J. B. (2019). The use of acoustic emission to diagnosis of fuel injection pumps of marine diesel engines. *Energies*, *12*(24), 4661.
4. Cornel, D., Gutiérrez Guzmán, F., Jacobs, G., & Neumann, S. (2021). Condition monitoring of roller bearings using acoustic emission. *Wind Energy Science*, *6*(2), 367-376.
5. H Alkhadafe, A Al-Habaibeh, S Daihzong and A Lotfi, Optimising Sensor Location for an nhanced Gearbox Condition Monitoring System, IOP Publishing,2012,364,PP 012077
6. Li, Y., Lee, C. G., & Xu, F. (2022). Acoustic emission sources localization and identification of complex metallic structures based on nearfield frequency space sparse decomposition. *Structural Control and Health Monitoring*, *29*(11), e3064.
7. Michael S. Packianather, Mark Eaton, Ioannis Papadopoulos, Theocharis Alexopoulos, Optimizing the number of acoustic emission sensors using the bees algorithm for detecting surface fractures, procedia CIRP, 2018, 67, pp 362-367.
8. Ono, K. (2019). Structural health monitoring of large structures using acoustic emission–case histories. *Applied Sciences*, *9*(21), 4602.
9. Randolph L. Moses, Robert M. Patterson, and Wendy Garber, Self Localization of Acoustic Sensor Networks, Approved for public release; distribution is unlimited,2015
10. S. Cyrille, "Sensor placement for modal identification", Mechanical Systems and Signal Processing, Vol. 27, pp-461 –470, 2012.

11. Sikorski, W. (2018). Active dielectric window: A new concept of combined acoustic emission and electromagnetic partial discharge detector for power transformers. *Energies*, *12*(1), 115.
12. Sikorski, W. (2019). Development of acoustic emission sensor optimized for partial discharge monitoring in power transformers. *Sensors*, *19*(8), 1865.
13. Stella-Rita. Optimum sensor placement for source localization and monitoring from received signal strength. Theses and Dissertations. 2010.
14. Thomas Glotzbach. David Moreno-Salinas, Optimal Sensor Placement for Acoustic Range-Based Underwater Robot Positioning, IFAC Conference on Control Applications in Marine Systems The International Federation of Automatic Control, Vol 9, 2013, pp 17-20.
15. Xu, X., Yan, X., Yang, K., Zhao, J., Sheng, C., & Yuan, C. (2021). Review of condition monitoring and fault diagnosis for marine power systems. Transportation Safety and Environment, 3(2), 85-102.
16. Zeng, D. (2021). Design of a Real-Time Wireless Sensing Monitoring System Based on Acoustic Emission Power GIS Equipment. *Journal of Sensors*, *2021*.