ABSTRACT

Reliable tracking of the plume by the robot is the key to achieving plume source localization. To address the problem of low success rate and long search time of robot source location due to the unavailability of reliable information on gas diffusion flow direction and flow velocity in an indoor weak wind environment, a hybrid strategy is proposed to improve the grey wolf optimization algorithm for robot plume tracking and location. The plume is modeled using Computational Fluid Dynamics (CFD) in a two-dimensional indoor weak wind environment, and the plume concentration value is used as the individual adaptation degree of the algorithm. Without carrying plume velocity and flow direction sensors, the source-finding robot simulates the grey wolf population’s social mechanism and hunting behavior to update its position. The improved Grey Wolf Optimization algorithm is compared with the traditional Grey Wolf Optimization (GWO), Particle Swarm Algorithm (PSO), and Genetic Algorithm (GA) in simulation experiments. The simulation experiments show that the average number of iterations of the improved GWO is 7, 108, and 118 times shorter than the four source finding algorithms of GWO, PSO, and GA. The average planning path is reduced by 0.91 meters, 2.35 meters, and 2.90 meters. 3s, 10.3s, and 9.3s reduce the average running time. The average positioning success rate is improved by 30%, 32%, and 40%. The applicability and Stability of the improved GWO algorithm in solving the plume tracking and localization problem in an indoor weak wind environment are verified.

INDEX TERMS

Robot, plume, CFD, tracking and positioning, indoor weak wind environment.

I. INTRODUCTION

China is currently in a period of rapid industrialization. As many enterprises do not manage the storage, transportation, and use of large quantities of hazardous chemicals properly daily, chemical leaks caused by various factors have led to numerous accidents, such as fires and explosions. Major safety accidents caused by the leakage of flammable and explosive toxic gases also occur frequently, especially in storage sites where large quantities of hazardous chemicals are stacked. Accidents often have a significant negative impact on society and the environment [1], [2]. To accurately locate the source of contamination within a short time, effectively control the scope of contamination, make timely warnings and evacuate personnel, and reduce economic and property losses to the greatest extent possible [3]. Research on how to locate the source of flammable and explosive toxic gas leaks has become an urgent problem in the field of public safety.

A plume [4] is a material plume created by the spread of a spill through a medium. Rapid identification of indoor plume sources, based primarily on plume concentration distribution, is a requirement and fundamental to effective control and mitigation strategies [5], [6]. The identification of the release intensity of time-varying pollutants with a known indoor...
source site was studied in the literature [7], [8], [9], [10] Lu et al. established a collaborative control system for coordinating multi-robot plans to find odor sources and then tested the control system’s reliability with experiments. Che et al. [11] proposed a multi-robot odor source location technique based on an improved ant colony optimization algorithm. Ji et al. [12] suggested MEGI-taxis as a new search algorithm, and experimental results revealed that it was superior in terms of average search time and success rate. To check the authenticity of the source, Zhu et al. [13] proposed a statistical-based source determination technique, followed by an artificial potential field method to remove the pseudo-source induced interference. Zhang et al. [14] established a multi-robot collaborative process based on small-habitat particle swarm optimization, and experimental results confirmed the approach’s efficiency. Shi et al. [15] used an improved genetic optimization approach to detect the odor source in the plume more rapidly and accurately. S et al. [16] applied the standard grey wolf optimization approach in a Gaussian plume model. They showed that it was operational and successful in plume tracking through experimental validation, although there are still issues, such as slow convergence in the late stage.

The indoor plume concentration distribution is mainly governed by the indoor flow field, the location of the plume source release, and the intensity of the plume source release. In the case of an indoor steady-state flow field where the area of the plume source is known, the pollutant concentration distribution is governed by the intensity of the plume source release [8]. In practice, the location of the head may be unknown, considering that wind direction and speed information is not significant in a weak wind field or free diffusion environment. This paper uses CFD to establish a two-dimensional indoor plume concentration distribution in a soft wind environment. By analyzing the implementation mechanism of GWO, a hybrid strategy is proposed to improve the grey wolf optimization algorithm for robot plume tracking and localization. The source-finding robot uses the gas concentration values as individual fitness and iterates the position update according to the personal fitness. Without using plume flow direction/velocity sensors, the source-finding robot simulates the social mechanism and hunting behavior of grey wolves to improve the search efficiency and reliability of plume tracking and localization in weak wind conditions.

II. PLUME CFD MODEL
A. PLUME CFD CONTROL EQUATION SET
The Gaussian plume/puff model [18], the SUTTON model [19], and the FEM3 model [20] are the primary models researched for numerical calculations of flammable gas leaks. Each model has its own adapt conditions, primarily based on the pattern of flammable gas diffusion in the atmosphere. This work focuses on a traditional plume leak that occurs inside a weak wind environment and assumes a continuous leak at the plume’s source. A variety of factors influence the concentration field distribution of the indoor plume dispersion. As a result, CFD is utilized to simulate a light wind condition indoors. The airflow motion in a simple mechanical ventilation model room and the plume concentration distribution from the emission of hydrogen sulfide gas as a simulated hazardous gas would be modeled in a system of energy k-equations. The component control equations [21], [22] control the indoor plume flow.

1) GAS EQUATION OF STATE

\[ P = \rho RT \] (1)

2) CONSERVATION OF ENERGY EQUATION

\[ \frac{\partial \rho}{\partial t} + \nabla (\rho V) = 0 \] (2)

3) ENERGY CONSERVATION EQUATION

\[ u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} + w \frac{\partial T}{\partial z} = a \left( \frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2} \right) \] (3)

4) RNG K-E EQUATION

\[ \frac{\partial (\rho u_i)}{\partial x_i} = \frac{\partial}{\partial x_j} \left( \alpha_k \mu_{\text{eff}} \frac{\partial k}{\partial x_j} \right) - \rho \varepsilon + G_k \] (4)

\[ \frac{\partial (\rho \varepsilon)}{\partial t} \frac{\partial}{\partial x_i} (\rho \varepsilon u_i) = \frac{\partial}{\partial x_j} \left( \alpha_{\varepsilon} \mu_{\text{eff}} \frac{\partial \varepsilon}{\partial x_j} \right) \]

\[ + 1.42 \frac{\varepsilon}{k} G_k - 1.68 \rho \frac{k^2}{\varepsilon} \] (5)

\[ \mu_{\text{eff}} = \mu + \mu_i = \mu + 0.0845 \rho \frac{k^2}{\varepsilon} \] (6)

\[ G_k = \mu_t \left( \frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) \frac{\partial u_i}{\partial x_j} \]

\[ = 0.0845 \rho \frac{k^2}{\varepsilon} \left( \frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) \frac{\partial u_i}{\partial x_j} \] (7)

where \( u \) is the x-axis velocity component, m/s; \( v \) is the y-axis velocity component, m/s; \( w \) is the z-axis velocity component, m/s; \( \rho \) is the gas density, kg/m\(^3\); \( u_i \) is the i direction velocity component, m/s; \( u_j \) is the j direction velocity component, m/s; \( \rho \) is the pressure, pa; \( R \) is the gas constant of a gas, J/(kg·k); \( u \) is the kinetic viscosity, m\(^2\)/s; \( T \) is the thermodynamic temperature, k; \( \alpha \) is the thermal diffusion coefficient, m\(^2\)/s; \( k \) is the turbulent kinetic energy, m\(^2\)/s\(^2\); \( \varepsilon \) is the effective kinetic viscosity, kg/(m·s); \( \xi \) is the dissipation rate, m\(^3\)/s\(^3\); \( G_k \) is the term for the generation of rough kinetic energy k due to the mean velocity gradient, kg/(m·s\(^3\)); \( \alpha \varepsilon \) is the Planter number corresponding to the dissipation rate; \( u_i \) is the turbulent kinetic viscosity, kg/(m·s); \( I \) are the tensor symbols, which take values in the range 1, 2.

B. PHYSICAL MODEL
A university postgraduate laboratory is abstracted and simplified in a 10 m (length) × 8 m (width) rectangle model
chamber according to the actual calculation requirements. One H2S leaking device is inserted as a simulated leakage source in this paper’s simulation. Figure 1 shows the model of the 1.5 m air intake and 1.5 m air outflow.

III. PLUME TRACKING AND POSITIONING METHODS

A. GREY WOLF OPTIMIZATION

Grey Wolf Optimization (GWO) [23] is a new intelligent optimization algorithm that simulates the predatory behavior of the grey wolf pack in nature. The gray wolf population has a strict hierarchy, which can be divided into four levels: $\alpha$, $\beta$, $\delta$, and $\omega$. Among them, the head wolf $\alpha$ is located as the leader of the population, and the wolf $\beta$ is mainly responsible for assisting the wolf $\alpha$ in decision-making; the wolf $\delta$ is accountable for tasks such as scouting, sentry, and guarding; and the wolf $\omega$ is the other alternative wolves, which are jointly guided by $\alpha$, $\beta$, and $\delta$ gray wolves. Gray wolf pack hunting mainly includes three stages: chasing prey, encircling prey, and attacking game. Its social mechanism is shown in figure 2.

1) PURSUIT OF PREY

The encircling behavior of GWO first determines the distance between the gray wolf and the prey and updates the position of the gray wolf with the following mathematical expressions (8) to (12).

$$D = \left| C \cdot X_p(t) - X_i(t) \right|$$

$$X_i(t + 1) = X_p(t) - A \cdot D$$

where: $t$ denotes the current number of iterations; $D$ denotes the distance between the gray wolf and the prey; $X_p(t)$ is the position of the game in the $t$ generation; $X_i(t)$ is the position vector of a single gray wolf in the first generation; $A$ and $C$ is the random constant coefficient, which is calculated as:

$$A = 2ar_1 - a$$

$$C = 2r_2$$

$r_1$ and $r_2$ is the random number between; the value decreases from 2 to 0 as the number of iterations increases, the expression is:

$$a = 2 - \frac{2t}{t_{max}}$$

where $t$ is the current number of iterations; $t_{max}$ is the maximum number of iterations.

2) SURROUNDING THE PREY

Grey wolves can identify the location of prey and surround them. Once the grey wolf has identified the location of the prey, it guides the pack, $\beta$ and $\delta$ led by the $\alpha$ wolf, to surround the prey. These three positions are used to determine the location of the prey, while the other individual grey wolves are guided to update their position according to the position of the individual wolf, gradually approaching the prey. The location update mechanism is shown in figure 3. The mathematical expression for this is (13) to (19).

$$D_\alpha = \left| C_1 \cdot X_\alpha(t) - X_i(t) \right|$$

$$D_\beta = \left| C_2 \cdot X_\beta(t) - X_i(t) \right|$$

$$D_\delta = \left| C_3 \cdot X_\delta(t) - X_i(t) \right|$$
where: $X_A$, $X_\beta$ and $X_\delta$ are the $\alpha$ wolf, $\beta$ wolf and $\delta$ wolf position respectively; $D_A$, $D_\beta$ and $D_\delta$ are the distances between individual wolves and $\alpha$ wolf, $\beta$ wolf and $\delta$ wolf respectively; $X_1$, $X_2$ and $X_3$ are used to calculate the motion trajectories of the three head wolves respectively; $X_i(t+1)$ are the updated positions of gray wolves. The GWO algorithm updates the wolf position through an iterative process, gradually approaching the prey and completing the predation on the target.

**B. HYBRID STRATEGY TO IMPROVE THE GREY WOLF OPTIMIZATION ALGORITHM**

1) POPULATION INITIALIZATION

Uniform distribution of the initial population ensures diversity and the traversal of the people. It improves the search efficiency of the algorithm, which is challenging to do when utilizing random initialization of population members in traditional GWO. The Good-node [24] is a consistently distributed and practical approach to choosing points, and using its uniformity to initialize the population can boost the population’s diversity. Figure 4 depicts the comparing results. Because using Good-node to establish the population has been successfully used in many intelligent algorithms [25], [26], this work uses Good-node to initialize the GWO population.

2) CELLULAR AUTOMATION

This paper addresses the shortcomings of the grey wolf algorithm, which is prone to local optimal and slow
convergence, by introducing the evolutionary rules of meta-
cellular automata for optimal population selection, and com-
paring and replacing the evolved fitness with the current
optimal fitness so that the grey wolf population can jump out
of local optimal.
A cellular automaton (CA) represents a temporally and
spatially discrete dynamical system in which individual cells
scattered in a regular grid take on a finite number of discrete
states, follow the same rules of action, and are synchronized
by defined local laws for updating. The set of cells around
an individual tuple, defined according to the corresponding
regulations, are called neighbors, and the next stage of the
current tuple is determined according to its state and that of
its neighbors [27], [28].
The cellular automaton consists of five parts: the cell, i.e.,
the primary cell, this paper improves the algorithm to use
the plume concentration value as the cell; the cell space,
which represents the d-dimensional grid space of the cell dis-
tribution; this paper takes the two-dimensional quadrilateral
grid space for plume source location; the neighborhood (N),
the set of all cells in the area of each cell, denoted as
N = (s1, s2, . . . sn), denotes the number of neighboring cells,
the value of n varies for different cell neighboring models,
standard models include Van Neumann type, Moore type
and the extended Moore type used in this paper, the three
neighboring models are shown in figure 5 evolution then
(f) that is, the cell state transfer function, according to the
current cell state and neighboring cell state to determine the
next moment state, specified as equation (20):

\[ S_{t+1}^i = f\left(S_t^i, S_{t+1}^n\right) \] (20)

The rules for meta-cell evolution are:
(1) Based on the extended Moore neighborhood model in
figure 5, the central cell of the shaded area is selected,
and the optimum plume concentration (fitness) for all
regions is calculated as the initial value,

\[ V_{ibest} = \min(f(s_{iq}), f(s_{iq}), \ldots f(s_{iq})) \] (21)

where s_{iq} is the judged value of the plume concentration.
(2) For a single region \( M_i \) take any of the cells
\( C_i \), compute \( V_i = f(s_1), f(s_2), \ldots f(s_n) \), if

FIGURE 6. Leakage concentration clouds at different moments.
FIGURE 7. Fitness curve and moving trajectory of sourcing robot based on GWO algorithm.

\[ V_i < V_{ibest}, \text{then } V_i < V_{ibest}, \text{and record and replace the labels; otherwise, no replacement is performed.} \]

3) PSEUDOCODE STEPS FOR A HYBRID STRATEGY TO THE ALGORITHM

The pseudocode stages for enhancing GWO with the hybrid strategy presented in this paper are shown in table 1 by combining the preceding descriptions of the hybrid improvement method descriptions.

IV. SIMULATION AND ANALYSIS OF RESULTS

A. PLUME MODEL SIMULATION AND RESULTS ANALYSIS

The simulated \( t_0 = 0 \) moments were released with a mass fraction of \( M = 0.04 \text{ kg/s} \), an inlet air velocity of \( v = 0.3 \text{ m/s} \), and an outlet pressure value of 0 Pa. The simulation conditions, as shown in Table 2, The two-dimensional indoor plume was simulated by CFD \( T = 54s, 180s, 360s, 600s \) four moments concentration dispersion clouds. As the gas has a certain turbulent velocity after the leak it keeps moving forward 54s or so. The gas gathers on both sides of the wall,

| TABLE 1. Improved GWO pseudo-code steps. |
|-------------------------------------------|
| Step 1: Improve gray wolf algorithm population initialization, set gray wolf population size, the maximum number of iterations. |
| Step 2: Initialize A, a, C. |
| Step 3: The plume concentration value was used as the individual fitness value to find the fitness value. |
| Step 4: Using the plume concentration value as the personal fitness, the fitness value was obtained and ranked, and the top three gray wolf individuals were recorded as \( a, \beta, \gamma \). |
| Step 5: while (\(<\) Max number of Iterations) |
| Step 6: for Iterate through each wolf |
| Step 7: Update the current gray wolf location |
| Step 8: end for |
| Step 9: Update A, a, C. |
| Step 10: Calculate the fitness of all gray wolves per individual |
| Step 11: Calculating the best fit and updating the position of individual head wolves, update \( X_a, X_\beta \) and \( X_\gamma \). |
| Step 12: \( I = I + 1 \) |
| Step 13: end |
away from the leak source. Later on, as the duration of the leak increases, the concentration values gradually increase at the leak source and in the surrounding area. The concentration of the plume at the inlet location is almost zero due to the weak wind; the simulated concentration clouds of the H2S leak at different moments are shown in figure 6.

**B. PLUME TRACKING AND POSITIONING SIMULATION RESULTS AND ANALYSIS**

To verify that the improved GWO can better locate the plume source by free diffusion of the gas alone in a weak indoor wind environment, the enhanced GWO was applied to active olfactory plume tracking and positioning with GWO, PSO and GA and compared to simulation experiments. Since CFD software cannot simulate a mobile robot, the plume concentration data of the CFD simulation plume model at different times are exported in csv format and then imported into Simulation Software, which is converted into plume concentration clouds at other times by means of interpolation. Then the plume tracking algorithm is integrated on its concentration clouds to achieve plume tracking in an indoor weak wind environment. And positioning simulation experiments.

To avoid the influence of randomness on the simulation experiments, the indoor plume concentration fields at $T = 300s$ and $T = 420s$ were taken as the simulation cloud environment for the four source-finding algorithms in the plume CFD simulation model. 50 plume tracking and positioning simulation experiments were carried out in Simulation software using the source-finding robot. The initial position of

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**TABLE 2. Plum model simulation conditions.**

| Inlet air velocity / (m s$^{-1}$) | Outlet pressure / Pa | H2S Leakage / kg s$^{-1}$ | Leak source | Spill time / s |
|----------------------------------|----------------------|--------------------------|-------------|--------------|
| 0.3                              | 0                    | 0.04                     | (0.5,3.9)   | 600          |
the source finding robot was (0.3,7.5), and the plume source position was (9.5,3.9). The plume tracking and positioning simulation results for the four source finding algorithms are shown in figure 7 to figure 10.

The parameters of the four algorithms are set as follows: the population size of each algorithm is 20, the maximum number of iterations is 200; the initial value of the convergence factor of the grey wolf optimization algorithm is set to 2; the inertia weight of the particle swarm algorithm is set to 0.8, the velocity factor is set to 2, and the learning factor is set to 2; the crossover probability of the genetic algorithm is set to 0.8, and the variation probability is set to 0.07. The number of iterations is set to less than or equal to 200. The number of iterations is less than or equal to 200, and the source finding time is less than or equal to 120 s. If the source finding is successful, the plume is considered as successful. Otherwise, it is considered a failure. In the simulation experiments, the source-seeking robot is approximated as a point, which is the “ideal robot.” The source-seeking robot can know its own coordinates and accurately follow the path planned by the source-seeking algorithm to track and locate the plume.

As seen in figure 7 the GWO algorithm successfully located the plume source after 27 and 23 position updates in the plume turbulence environment at T = 300s and T = 420s, respectively, without relying on the plume velocity and flow direction sensors. As seen in figure 7, the concentration changes over a more extended period are small, so the original grey wolf algorithm still suffers from slow convergence and falls into a local optimum, leading to a low success rate in the final plume tracking and localization.

As seen in figure 8, the PSO-based algorithm successfully located the plume source after 190 and 172 position updates at T = 300s and T = 420s, respectively, in the indoor weak wind plume environment without relying on the plume velocity and flow direction sensors. The PSO algorithm does not require coding in the source finding process compared to
the GA algorithm and preserves the optimal solution. Still, its convergence is random, the search tends to stall, and the algorithm tends to fall into a local optimum, resulting in a low success rate of the PSO algorithm in source finding.

As seen in figure 9, the plume source was successfully located after 153 and 192 position updates based on the GA algorithm in the indoor weak wind plume environment at $T = 300s$ and $T = 420s$, respectively, without relying on the plume velocity and flow direction sensors. The GA algorithm needs to be encoded and decoded first in the source finding process, resulting in a high complexity of the algorithm, which has a low success rate in the head finding and location of the plume and is challenging to set up as the performance of the algorithm is greatly influenced by the parameters.

As seen in figure 10, Without relying on the plume velocity and flow direction sensors, the plume source was successfully located after 12 and 14 position updates based on the improved GWO algorithm at $T = 300s$ and $T = 420s$, respectively, in the indoor weak wind plume environment. The improved grey wolf algorithm makes the particles initially more homogeneous due to a good set of points for their initialization. At the same time, the target locations across the plume range become easy to determine using cellular automation, avoiding premature convergence of the wolf pack and trapping the algorithm in a local optimum.

In summary, the four source finding algorithms based on the improved GWO, GWO, PSO, and GA can all plan different paths and successfully locate the source of the plume at other times and different numbers of iterations, as can be seen from the fitness curves, the four algorithms can optimize at the local optimum solution: as the number of iterations grows they continue to jump out of the local optimum and eventually converge to the global optimum. However, the improved GWO has better performance in plume tracking and localization. Four source-finding algorithms were recorded to track the plume and successfully locate the data under
the constraints. The simulation results data are shown in tables 3 and tables 4.

Tables 3 and tables 4 show that the four source finding algorithms, GWO, PSO, and GA, have specific applicability and autonomy in solving the plume tracking and positioning problem in indoor plume turbulence at $T = 300s$ and $T = 420s$. However, due to the limitations of the traditional source finding optimization algorithms, which fall into "premature convergence" and the poor balance between local and global search, the robot plume tracking and localization methods based on the GWO, PSO, and GA search strategies are less efficient than the improved Grey Wolf optimization algorithm in terms of an average number of iterations, average planning path distance, and average running time in the simulation experiments. The average success rates of the four source finding algorithms were 100%, 68%, 66%, and 54% versus 100%, 70%, 68%, and 60% at two moments, respectively. The simulation data shows that the improved grey wolf positioning algorithm can be more effective for plume source tracking and positioning.

V. CONCLUSION

To solve the plume source positioning problem in an indoor plume turbulence environment, the indoor plume turbulence environment is modeled in CFD. The use of plume velocity and flow direction sensors in the traditional plume tracking and localization method is eliminated due to the unavailability of plume velocity and flow direction information, and an improved GWO method for autonomous plume source localization is proposed. It is verified through simulation experiments; the average number of iterations of the improved GWO is reduced by 8, 110 and 134 compared with the four source finding algorithms of GWO, PSO and GA, respectively. The average planning path is shortened by 0.91m, 2.35m and 2.90m respectively. The average running time is shortened by 3s, 10.3s and 3.05s. The average success rate is improved by 30%, 32%, and 40%. The operability and robustness of the mobile robot plume tracking method with an improved GWO algorithm in solving the plume tracking problem in a turbulent indoor environment is verified. Future research will investigate plume tracking and positioning under strong indoor winds and plume source positioning methods in 3D environments.

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TABLE 3. Plume tracking simulation results based on improved GWO, GWO, PSO, and GA algorithm at 300s moment.

| Algorithm /Strategy | Average iterations /n | Min distance /m | Max distance /m | Average distance /m | Min Time /s | Max Time /s | Average Time /s | Success Rate /% |
|---------------------|-----------------------|----------------|----------------|---------------------|-------------|-------------|----------------|----------------|
| Improved GWO        | 10                    | 6.34           | 19.20          | 12.15               | 3.0         | 10          | 6              | 100            |
| GWO                 | 18                    | 9.31           | 20.18          | 12.42               | 4.2         | 11          | 9              | 68             |
| PSO                 | 125                   | 9.23           | 22.46          | 13.58               | 4.3         | 52.3        | 18.6           | 66             |
| GA                  | 163                   | 8.36           | 21.36          | 15.2                | 5.2         | 30.4        | 15.3           | 54             |

TABLE 4. Plume tracking simulation results based on improved GWO, GWO, PSO, and GA algorithm at 420s moment.

| Algorithm /Strategy | Average iterations /n | Min distance /m | Max distance /m | Average distance /m | Min Time /s | Max Time /s | Average Time /s | Success Rate /% |
|---------------------|-----------------------|----------------|----------------|---------------------|-------------|-------------|----------------|----------------|
| Improved GWO        | 10                    | 7.65           | 20.13          | 11.65               | 3.0         | 10.5        | 5.2            | 100            |
| GWO                 | 22                    | 8.82           | 21.73          | 12.56               | 4.4         | 17.3        | 9.4            | 70             |
| PSO                 | 120                   | 8.56           | 21.36          | 14                  | 5.2         | 50          | 15.5           | 68             |
| GA                  | 144                   | 8.66           | 22.18          | 13.90               | 3.3         | 27          | 16.2           | 60             |
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