Coverage Optimizing of Cyber-Physical System for Coal Mine Fire Detection

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Abstract: The present research has proposed an efficient coverage optimization strategy for cyber-physical system (CPS) on the basis of probability measuring and thermal detection range model, in order to improve the performance and achieve the maximization coverage rate of covert fire detection system in coal mine gob. A modified particle swarm optimization algorithm is chosen to perform an optimal design. Computational performances of different methods and coals are investigated and the influence of sensor errors on computational accuracy is compared. The results show that the proposed algorithm can guarantee the convergence of the global optimization coverage rate, and is proved to be superior in terms of searching quality and speed.

Keywords: cyber-physical system, safety monitoring, coal mine fire, wireless sensor networks, coverage rate optimization.

1. INTRODUCTION

Because of the covert fire source, the complex restriction of the geological conditions, and so on, proving up the location and extension of the underground fire area has been the question that the project of extinguishing fire should make definite (Stracher, 2004). For danger alarm requirement, the long-distance monitoring system and wireless sensor network should be operated. The wireless sensor network which has emerged as a promising tool for monitoring the physical world is one of the most important cyber physical systems (Tang, 2008). It can be deployed rapidly and cheaply, thereby enabling large-scale, on-demand monitoring and tracking over a wide range of applications such as danger alarm, vehicle tracking and so on.

The most important application of monitoring system in the underground coal mine is the covert fire source detection caused by coal spontaneous combustion. It reports that among Chinese state-owned collieries, 56% of the mines have been jeopardized by spontaneous combustion, and accounts for 90–94% of the total coal mine fires (Li, 1998). The most widespread method of detecting the onset and development of a spontaneous combustion is by monitoring gas concentrations in return airway (Adamus, 2011). But the method can not determine the position of covert fire in the gob stink of coal mine.

When air is allowed to percolate through many organic materials including coal then there will be a measurable rise in temperature. Although spontaneous coals could produce heat and an observable elevation in temperature in the gob stink of underground coal mine, it's still very difficult to determine the position of the covert fire source. Because the thermal conductivity of coal and crushed rock is very low, the temperature even within a meter of active centre of heating may indicate no abnormal condition (Sahu, 2011). Therefore, a wireless monitoring system which used to determine increases in temperature in gob stink should consist of lots of thermal sensor devices. In practice, the sensor nodes are often arranged in uniform distributions in coal mine gob. It may cause the coverage rate problem when the fire source position is out of sensitive range of every thermal sensor.

The coverage problem which can be considered as the measure of quality of system in a sensor network directly affects the capability and efficiency of the sensor network (Živanov, 2008). Current solutions are based on the main idea of finding the optimal location of active nodes while maintaining coverage and connectivity. Several algorithms and various retrieving techniques have been applied to find a close-to-optimal solution based on local information. The particle swarm optimization (PSO) algorithm (Kennedy, 2007) is able to find global optimum solutions or good approximate solutions, usually without theoretical proof. This is solely due to its ability to explore the search domain with 'jumps' from one local solution to others, and thus the global optimum solution can be reached step by step. The PSO algorithm has been studied extensively by many researchers in recent years. The basic PSO method has been proved that it can guarantee convergence, but not a global optimum (Clerc, 2002). In order to guarantee the convergence of the global optimum solution, several modified PSO algorithms have been developed (Yuan, 2010, 2011).

In this paper, an optimization strategy of the WSN's coverage rate for temperature detection system in coal mine gob is presented. In the next section, the temperature sensitive range and the coverage rate model for WSN of the monitoring system in mine gob is discussed. Section 3 proposes a modified PSO algorithm with a stochastic selection to guarantee convergence to global optimum solutions. The simulation results and discussions are shown in Section 4. Finally, Section 5 describes the conclusions.

2. THERMAL SENSOR COVERAGE MODEL

The fundamental problem for a thermal sensor node in coal mine gob is the effective detection range for temperature increasing. And the temperature distributions in the gob are decided by the heat transfer. In considering one-dimensional non-steady coupled radiative and conductive heat transfers, the general form of the energy equation of the internal radiation and the transient coupled conductive heat transfer is found to be (Tan, 2004):

$$\rho c \frac{\partial T}{\partial t} = \frac{\partial}{\partial x}(k_c \frac{\partial T}{\partial x}) - \operatorname{div}\mathbf{\Phi}^r \quad (1)$$

where k_c is thermal conductivity, $\mathbf{\Phi}^r(T)$ is the thermal radiation source term.

$$\begin{aligned}\mathbf{\Phi}^r(T) &= \int_{\Delta V} -\operatorname{div}\mathbf{q}^r \,\mathrm{d}V \\ &= \int_{\Delta V} -\kappa_a\left[4\pi I_b(\tau) - G(\tau)\right]\mathrm{d}V\end{aligned}$$

(2)

Here, the incident radiative power $G(\tau) = \int_{\Omega} I(\tau,\Omega)\,\mathrm{d}\Omega$ can be transformed to $G(\tau) = 2\pi\int_{-1}^{1} I(\tau,\mu)d\mu$. The radiative intensity $I(\tau,\Omega)$ can be solved by the radiative transfer equation for one-dimensional absorbing, emitting and scattering grey medium. It can be expressed as:

$$\begin{aligned}\mu\frac{dI(\tau,\mu)}{d\tau} &= -I(\tau,\mu) + (1-\omega)I_b(\tau) \\ &\quad + \frac{\omega}{2}\int_{-1}^{1} I(\tau,\mu')\Phi(\mu',\mu)d\mu'\end{aligned}$$

(3)

where τ is the optical thickness given by $\tau = (\kappa_a + \kappa_s)L$, ω is the scattering albedo with $\omega = \kappa_s/(\kappa_a + \kappa_s)$, L is the medium thickness, and κ_a and κ_s are the absorbing and scattering coefficient, respectively.

For the second boundary condition, one boundary is defined as heat flux boundary by fire centre heating and the other one is adiabatic condition. The boundary conditions can be expressed as:

$$\left(k_c \frac{\partial T}{\partial x}\right)_{x=0} = q_c \quad (4\text{-a})$$

$$\left(k_c \frac{\partial T}{\partial x}\right)_{x=L} = 0 \quad (4\text{-b})$$

To solve the coupled radiative and conductive heat transfer equations (1) and (3), the triangular matrix algorithm and spherical harmonics method (Modest, 2008) are used. The detection range is determined in according to the numerical results of temperature distributions. Table 1 shows the detection range for different kinds of coals. Here, the minimum temperature rise which can be sensed by thermal sensor node is assumed as 0.1℃. It can be seen that the thermal conductivity of every coal makes the variable detection ranges.

Table 1. Detection ranges for different kinds of coal

Coal	Conductivity	Detection Range(m)
Lignite	0.953	4.95
Bituminous	0.562	3.21
anthracite	0.378	2.58

The coverage model of the wireless thermal sensor network could be established based on the detection range of sensor node which mentioned above. Assume m sensors are deployed in the random positions in a $k \times l$ sensor field. Each sensor has a detection range r , and sensor n_i is deployed at point (x_i, y_i) . For any point A at (x, y) , we denote the distance between n_i and A as

$$L_A(n_i) = (x - x_i)^2 + (y - y_i)^2 \quad (5)$$

It assumes that sensor readings have no associated uncertainty in reality, and sensor detections are imprecise. The coverage the coverage $C_A(n_i)$ of a grid point A by sensor n_i needs to be expressed in probabilistic terms; hence a precise detection model is introduced:

$$C_A(n_i) = \begin{cases} 1 & L_A(n_i) \le r - r_u \\ e^{-\alpha\lambda^{\beta}} & r - r_u < L_A(n_i) < r + r_u \\ 0 & L_A(n_i) \ge r + r_u \end{cases} \quad (6)$$

where r_u is a measure of uncertainty in the sensor detection, $r - r_u \ge 0$. α and β are parameters that measure detection probability when a target is at distance greater than r_u but within maximum from the sensor. When $r_u > 0$, the probabilistic sensor detection model is used. Due to the uncertainty in sensor detection responses, grid points are not uniformly covered with the same probability. Some grid points will have low coverage rate if they are covered only by one sensor and far from other sensors. In this case, it is necessary to overlap the sensor detection area to compensate for the low detection probability. Consider a grid point with coordinate (x, y) lying in the overlap region of sensors n_i and n_j . Since sensors within a cluster operate independently in their sensing activities, if neither n_i nor n_j covers grid point at (x, y) , obviously, the probability of the grid point being covered is denoted as:

$$C_A(n_i, n_j) = 1 - (1 - C_A(n_i))(1 - C_A(n_j)) \tag{7}$$

It can also be extended to a region which is overlapped by a set of n_s sensors, $n_s = \{n_1, n_1, \cdots, n_m\}$. The coverage in this case is given by:

$$C_A(n_s) = 1 - \prod_{i=1,m} (1 - C_A(n_i)) \tag{8}$$

The coverage rate for the entire grid of the sensor set n_s is calculated as follows:

$$C_{all}(n_s) = \sum_k \sum_l C_A(n_s) / (k \times l) \tag{9}$$

3. OPTIMIZATION ALGORITHM

In the optimal design for effective coverage of WSN in coal mine gob, the objective function of the problem in this paper can be written as：

$$F(n_s) = 1 - C_{all}(n_s) \tag{10}$$

Therefore the coverage problem is changing to fitness minimization. Several algorithms and various retrieving techniques have been applied to find a close-to-optimal solution. In this paper, the PSO method is employed. The basic idea of PSO can be described as each individual in the swarm aiming at a better position for itself subject to satisfying certain fitness criteria. According to the simple PSO model, at generation $t+1$, the velocity $V_i(t+1)$ for each dimension of the i th particle can be updated as follows:

$$\begin{aligned} V_i(t+1) = wV_i(t) + r_1c_1(P_i(t) - X_i(t)) \\ + r_2c_2(P_g(t) - X_i(t)) \end{aligned} \tag{11}$$

where w is the inertia weight coefficient; c_1 and c_2 are two positive constants called acceleration coefficients; $P_i(t)$ and $P_g(t)$ are local and global individual best locations, respectively; r_1 and r_2 are random numbers in the interval [0,1]. In the standard PSO, the particle swarm may stop evolving before finding the global solution and fall into so-called premature convergence. To avoid premature convergence, a modified PSO algorithm is present here. Setting the inertia weight $w = 0$ and the new particle position can be updated as:

$$\begin{aligned} X_i(t+1) = X_i(t) + c_1r_1[P_i(t) - X_i(t)] \\ + c_2r_2[P_g(t) - X_i(t)] \end{aligned} \tag{12}$$

To improve the global searching ability, $P_g(t)$ is maintained as the historic best position, and an extra particle labelled j with position $X_j(t)$ is generated randomly in the search domain. In this way, the following updating procedure is obtained:

$$\begin{cases} P_j(t) = X_j(t) \\ P_g(t) = \arg\min(P_i(t), P_j(t)) \end{cases} \tag{13}$$

This means that if $P_g(t+1) = P_j(t+1)$, the random particle j is located at the best position and the new random particle will be sought repeatedly. Therefore at least one particle is generated randomly in the search domain, thus improving the global searching ability.

The implementation of the SPSO approach for solving the problem of converge rate of WSN can be carried out according to the following procedures.

1. Input system data, and initialize a particle swarm. Input system configuration, control parameters such as the lower and upper bounds for the estimated parameters, randomly generate an initial random position for every sensor node in swarm particles. Set the index of iteration $t = 0$.

2. Calculate the fitness value. Calculate the fitness for each particle by substituting the position of each sensor node into the coverage calculation, the fitness value is set equal to the calculated value of the coverage rate of sensor network with all particle positions as arguments.

3. Compare the coverage rate value for each particle with a priori best $P_i(t-1)$. If the fitness value is lower than $P_i(t-1)$, set this value as the current $P_i(t)$, and record the corresponding particle and sensor node positions.

4. Choose the particle associated with the best $P_i(t)$ of all particles, and set the value as the current global best $P_g(t)$. Introduce a randomly-selected particle into the population, and update the particle position for each particle.

5. Check the stop criterion. If the pre-set maximum number of generations is reached or if no improvement to the best solution is obtained after a given number of iterations N_t , then the process is terminated; otherwise, increment the iteration index $t = t+1$, and loop to Step 2.

4. RESULTS AND DISCUSSIONS

In the first part of this section, the performance of the proposed SPSO is investigated through comparisons with the standard genetic algorithm (GA) and basic PSO method. Throughout these experiments, the communication radius is set as twice the sensing radius to ensure coverage connectivity. We place 20 potential sensor nodes in a 20×20 square field, and $r_u = 1\text{m}$, $\alpha = \beta = 0.5$. In this case, the detection range of lignite coal is chosen

The position of each node is initialized randomly in the solution space. The lower and upper bounds of position for each node are [-5,5]. The standard PSO sets $c_1 = c_2 = 2.05$ and uses a linearly varying inertia weight over generations, varying from 0.9 to 0.4. The c_1 and c_2 of SPSO are set to 2.0. The probabilities of mutation and crossover of GA are set to 0.3 and 0.6. All three methods use a population size of 50. The maximum generation number is 1000.

As shown in Fig.1, coverage rate value for the SPSO algorithm converge much faster than that for the standard PSO algorithm and GA. Moreover, the SPSO algorithm can arrive at the best coverage rate among the three methods within a smaller number of generations.

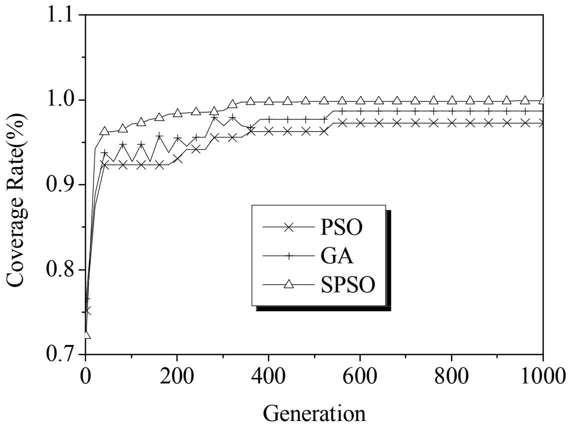

Fig. 1. Comparison of coverage rate for different methods.

Fig.2 displays the computation time using PSO and SPSO with different swarm size, SPSO method is less time-consuming than PSO given the same swarm size. Thus, the SPSO algorithm is superior in terms of searching quality and speed in deriving results.

Then, the influence of different coals on the optimization problem of coverage rate is examined. In Fig.3, it can be seen that the coverage rate value converges after 500 iterations for three coals. Assuming the mine gob is filling with the lignite coal, the coverage rate could be 100 percentages using 20 sensor nodes in the gob space. Meanwhile, the coverage rate of the gob filled with anthracite coal using the same sensor is only about 75% according to the smaller detection range. It means that the node number of thermal sensor network in the coal mine gob should consider the influence of the coal kind.

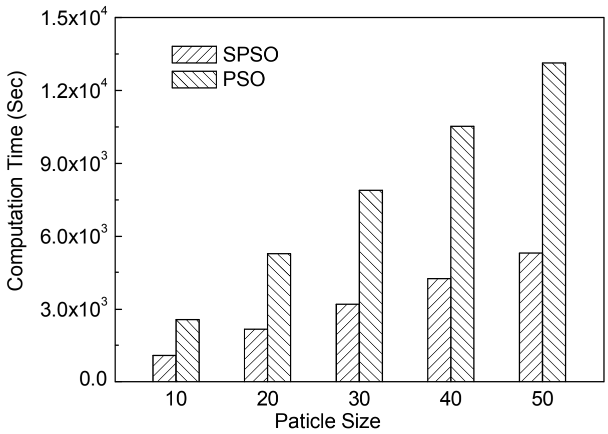

Fig. 2. Computation time comparison of PSO and SPSO with different swarm size.

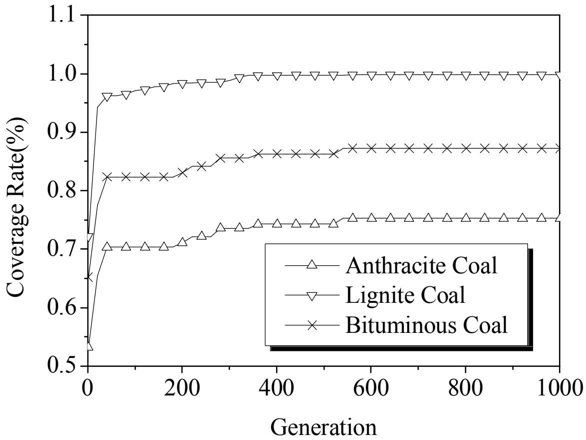

Fig. 3. Comparison of coverage rate for different coals.

In fact, each sensor has slight different sensing radius from the others. To demonstrate the effects of sensing error, random standard deviations are added to the sensing radius for every sensor. The following relation has been used in the present analysis:

$$r_{exact} = r_{mean} + \sigma\varsigma \tag{14}$$

Here, ς is a normal distribution random variable with zero mean and unit standard deviation. The standard deviation σ , for a $\gamma\%$ measured error at 99% confidence, is determined as

$$\sigma = \left(r_{mean} \times \gamma\%\right)/2.576 \tag{15}$$

From Fig.4, it can be seen that with increasing measured error $\gamma\%$, the effective coverage rate decreases. For $\gamma\% = 20\%$, the coverage rate may be reduced to 90%.

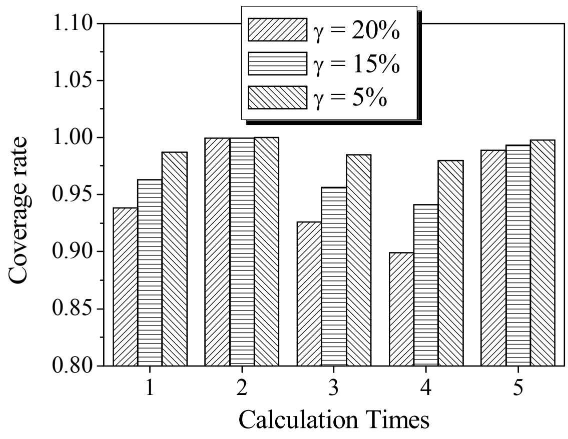

Fig. 4. Comparison of coverage rate with sensor error increased.

5. CONCLUSIONS

In this paper, the optimal design for the effective coverage of wireless sensor networks was investigated, in order to improve the network performance and increase coverage rate for the convert fire detection system in coal mine gob. For a practical approach, a precise probabilistic sensor detection model and detection range model for different coals were imported. A modified PSO algorithm with a stochastic selection to guarantee convergence to global optimum solutions was proposed. To verify the applicability of the SPSO algorithm to this problem, a series of tests had been performed. Through comparing the effect of different algorithms on the coverage rate, it was found that the SPSO algorithm is superior in terms of searching quality and speed in deriving results. The influences of different coals and measured error on the optimization problem of coverage rate were also examined. The effective coverage rate decreases with increasing measured error.

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