

Article

Risk and Energy Based Optimization for Fire Monitoring System in Utility Tunnel Using Cellular Automata

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Abstract: Fire is one of the biggest threats to the safety of utility tunnels, and establishing camera-based monitoring systems is conducive to early fire finding and better understanding of the evolution of tunnel fires. However, conventional monitoring systems are being faced with the challenge of high energy consumption. In this paper, the camera operation in a utility tunnel was optimized considering both fire risk and energy consumption. Three design variables were investigated, namely the camera sight, the number of cameras in simultaneous operation, and the duration of camera operation. Cellular automata were used as a simple but effective method to simulate the spread of fire in a utility tunnel. Results show that as the number of cameras in simultaneous operation increases, the probability of fire capture also increases, but the energy consumption decreases. A shorter duration of camera operation can lead to a higher probability of fire capture, and meanwhile, lower energy consumption. For the duration of camera operation shorter than or equal to the allowable time, the probability of fire capture is significantly higher than that for the duration longer than the allowable time. Increasing the camera sight will significantly increase the probability of fire capture and lower the total energy consumption when a blind monitoring area exists. The total energy consumption of a camera-based monitoring system roughly satisfies hyperbolic correlation with the duration of camera operation, while the probability of fire capture can be predicted based on the number of cameras in simultaneous operation through a power model. The optimal design for the modeled tunnel section is two cameras in simultaneous operation with a tangent monitoring area. The duration of camera operation should be as short as possible, at least shorter than the allowable time. The study is expected to provide a reference for the sustainable design of energy-saving utility tunnels with lower fire risk.

Keywords: utility tunnel; fire monitoring optimization; cellular automata; fire risk; energy consumption



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1. Introduction

Utility tunnels are facilities where electricity, gas, and telecommunications are incorporated and are an important infrastructure in modern cities [1]. Due to the special properties of the substances they carry, e.g., the flammability of natural gas, the tunnels are usually faced with a high risk of fire [2]. Since the tunnel is a semi-closed, long and narrow space, the fire can spread much faster and is much more difficult to locate and fight [3]. In fact, compared with other types of fires, tunnel fires are far more complex and generally cause more damage [4] than other hazards [5]. Therefore, it is essential to establish effective tunnel fire monitoring systems. As a response, numerous cameras or sensors have been equipped in tunnels to detect possible fires [6]. However, the current design specifications are incomplete [7], and it is supposed to be not possible to satisfy the requirements for early fire detection without an appropriate design of camera or sensor arrangement [8,9]. In this case, the optimization of camera or sensor layout and operation have been drawing increasing attention.

The optimization of sensor layout is a combinatorial optimization problem that can usually be solved through traditional optimization algorithms, sequence methods, and intelligent optimization algorithms [10]. Since both traditional optimization algorithms and sequence methods can only get suboptimal solutions, intelligent optimization algorithms are more widely used for such a problem. Commonly used intelligent optimization algorithms are usually swarm-based intelligence, including the particle swarm optimization (PSO) algorithm [11–14] and the ant colony optimization (ACO) algorithm [15]. These algorithms have been used to determine the tunnel fire sources and to optimize the sensor layout. Evolutionary-based algorithms like differential evolution (DE) [16] have also been employed to solve these problems, and hybrid algorithms [10] combining both evolutionary- and swarm-based algorithms have also been developed. In recent years, the advances in artificial intelligence (AI), machine learning [17], and AI modeling [18] have witnessed a rapid growth in the application of intelligent monitoring like fire source identification and optimal layout design [19,20]. These techniques may include artificial neural network (ANN) [21], convolutional neural network (CNN) [8,22], transpose convolution neural network (TCNN) [23], BP neural network [24,25], long short-term memory network (LSTM) [21,23,26] or LSTM recurrent neural network [27], bidirectional long short-term memory (BiLSTM) [28], random forests (RF) [26], as well as other machine learning algorithms like Bayesian network (BN), support vector regression (SVR), and multilayer perceptron (MLP) [26,29]. Different machine learning algorithms can also be employed in combinations like CNN–LSTM or CNN–BiLSTM [28]. In addition to the two mainstream methods of intelligent optimization and machine learning, the layouts of sensors can also be optimized through numerical simulation [30,31], and the performance of dynamic sensor networks has also been investigated [32,33]. It should be noted that even though for a tunnel there are theoretically an infinite number of possible layouts, evaluating only several common cases is believed to be acceptable for fast design in engineering practice [34].

A critical work in the optimization of sensor layout is to simulate the evolution of fire in tunnels. Fire scenarios can be modeled either by full-scale [17] and reduced-scale [35] tunnel fire tests. But since real tunnel fires are usually accompanied with multi-source burning [36], numerical methods are more often used [37–39], especially computational fluid dynamics (CFD) techniques [34,40,41]. These methods can simulate tunnel fire scenarios closer to reality, but on the other hand may occupy more computational resources. Thus, it is meaningful to find a way for tunnel fire modeling that takes less computation and in the meanwhile without loss of effectiveness.

Although there has been lots of studies on the optimization of sensor layout, the energy consumption of the designs has rarely been evaluated. In fact, the operation of the whole monitoring system, especially the storage of mass data generated, can consume much power. According to a survey conducted by Tianjin Municipal Engineering Design & Research Institute, the monitoring system is the main source of energy consumption in a smart utility tunnel, which accounts for around 68.8% of the total energy consumption. The biggest consumer is the building sector which uses quite a large amount of world energy [42–44], and it is of great significance to reduce such consumption to achieve the goal of sustainable development. However, the issue cannot be simply addressed simply by using less cameras or shortening the duration of operation, as the monitoring coverage should also be considered so that the tunnel fires can be detected in time. Therefore, that becomes an optimization for better trade-off. It should be noted that even though there exist various fire alarms or sensors, there is no conflict between using cameras and sensors, and using both cameras and sensors at the same time can improve the redundancy of the monitoring system. Actually, since the camera is usually a must in the utility tunnel, using cameras for fire monitoring will cause no extra costs. Instead, it may even cut the use of some distributed sensors, finally leading to lower total costs. Moreover, using cameras can significantly improve the reliability of the monitoring system as the sensors are prone to malfunction due to the problem of sensitivity: either misreporting a non-existent fire or making no response to the fires. In addition, commonly used fire sensors can send an alarm only when a nearby change in ambient conditions is detected. That means

a process of thermal conduction or gas diffusion is required, which takes time. Thus, cameras enable a more accurate and rapid response to fires. In addition, using cameras is also an effective way to obtain more details about fire evolution in utility tunnels.

In this paper, the camera operation in a utility tunnel was optimized considering both fire risk and energy consumption. A tunnel section with a dimension of 5×200 m was modelled with five cameras installed to form the fire monitoring system. The modelled utility tunnel was meshed into grids, and a cellular automata-based algorithm was then used to simulate the spread of a fire in the tunnel. Three design variables including the camera sight (R), the number of cameras in simultaneous operation (N), and the duration of camera operation (T) were examined. The effects of the three variables on fire capture and energy consumption were revealed, based on which the optimal design strategy for camera-based fire monitoring system was proposed. The study gives an effective method for significantly reducing the energy consumption of utility tunnels while maintaining a reliable fire monitoring capability, thereby leading to a design with more energy sustainability and lower fire risks.

2. Methodology

2.1. Fire Simulation

Fire simulation was achieved with a cellular automata method in this study. Compared with conventional fire simulation algorithms, the cellular automata method is an effective simplification, which takes much less computation while the yield simulation results are reliable for the engineering design. As illustrated in Figure 1, the utility tunnel was first meshed, in which one grid was randomly selected as the initial fire source (grid in red). The spread of fire was simulated through iteration. In each iteration, one burning grid can ignite 8 surrounding grids (grids in green) with a certain probability, which was set to be 1.0 in this study in case the fire burnt itself out. Once the surrounding grids become ignited, the fire source stops burning, and the corresponding area is labeled as ignited and cannot be ignited again. That means the burning of each grid can only last for one step, after which it cannot be re-ignited. When the fire enters the monitoring area of the cameras in operation, it gets captured. The total steps of iteration are recorded, and the algorithm ended.

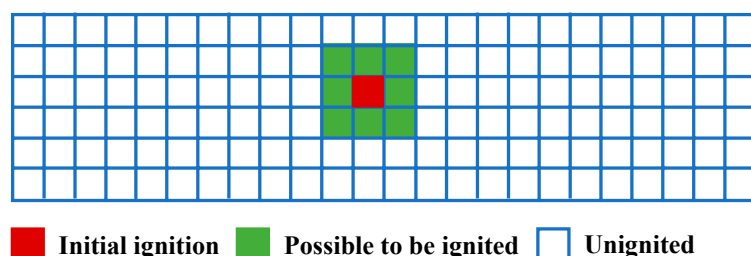


Figure 1. Schematic diagram for cellular automata-based fire simulation.

The utility tunnel investigated in this study is a section with the size of 5×200 m, and the arrangement of the cameras is shown in Figure 2. There are 5 cameras in total, with 50 m between each two. Apart from the two fixed cameras at the two ends of the tunnel section, the other three cameras are those that can rotate for 360° . For convenience, each rotating camera was simplified as two fixed cameras with one facing left and the other facing right. During operation, the two equivalent fixed cameras turn on and off alternately. The period of the rotating camera is assumed to be 2 steps and the rotation always starts from left to right. That is, the left equivalent fixed camera is first on for 1 step, and then turned off and the right one turned on. The right equivalent fixed camera works for 1 step, and then it is also turned off. Again, it then turns to the left one, and so on and so forth. In this way, the operation of the rotating camera can be simulated. The monitoring area of each camera can cover the full width of the tunnel section, and any fire within the camera sight along the tunnel length can be captured. The tunnel section was meshed into 50×2000 grids, with each grid measuring 10×10 cm in size. The maximum number of iterations was set to be 30,000 steps, which is enough for the whole section to become ignited.

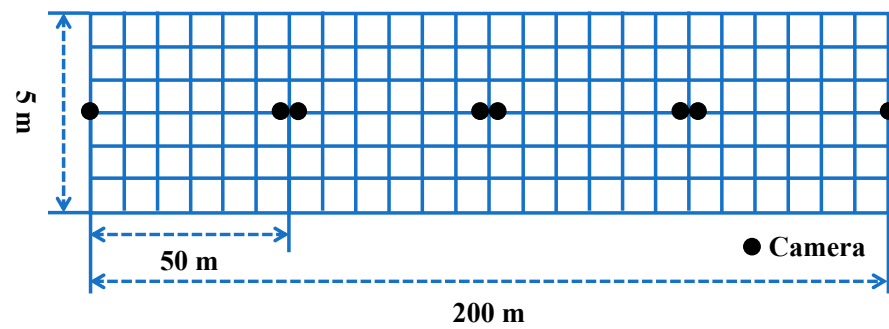


Figure 2. Arrangement of cameras.

For more clarity, an example is given herein to show how exactly the monitoring system works in this study. As illustrated in Figure 3, for each certain period of time, 2 cameras will be randomly selected to work (cameras highlighted in green). Grids in green represent the monitoring areas of the working cameras, where a darker color means the area in the current camera sight, while a lighter color means the area in the camera sight of the next (or the last) step, as the working strategy of the rotating camera simulated by two fixed cameras.

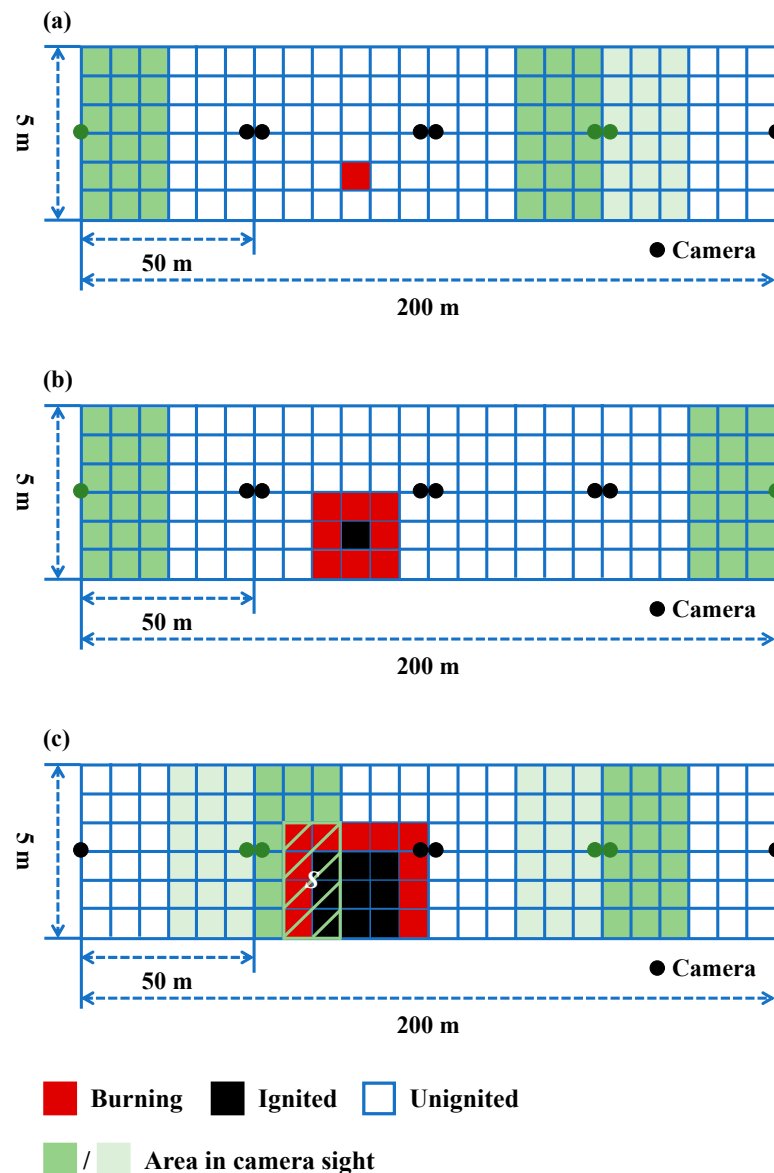


Figure 3. Schematic diagram for the operation of the monitoring system.

In Figure 3a, a grid is randomly selected as the initial fire source, as the grid in red. But since the grid is not in any monitoring area, the fire is not captured, and the algorithm continues. When it comes to Figure 3b, the initial fire has stopped burning after igniting the surrounding grids. But still, since the burning grids are not in the monitoring area, the fire has not been captured. Once the fire spreads into the monitoring area, as indicated by the shaded area *S* in Figure 3c, the fire is captured. Then the algorithm ends, and the total steps of iteration are recorded.

2.2. Design Variables

Three design variables were considered in this study, i.e., the camera sight (*R*), the number of cameras in simultaneous operation (*N*), and the duration of camera operation (*T*). For instance, *N* cameras in simultaneous operation with the duration of camera operation *T* means *N* cameras were randomly selected to work from the five for every *T* steps. The three design variables cover both the hardware (camera sight and camera number) and software (duration of operation) of the monitoring system and are believed to be the most important when considering the fire risk and energy consumption. The values of the three variables are given in Table 1, which were determined based on the commercially available cameras and engineering practice.

Table 1. Configuration for design variables.

Design Variables	Values
<i>R</i>	15 m
	20 m
	25 m
	30 m
	35 m
<i>N</i>	1
	2
	3
	4
<i>T</i>	50 Step
	100 Step
	150 Step
	200 Step
	250 Step

Note: The camera sight less than 25 m ($R < 25$ m) indicates cases with blind monitoring area, while that greater than 25 m ($R > 25$ m) indicates cases with overlapping monitoring area. A camera sight of 25 m ($R = 25$ m) indicates the case with tangent monitoring area.

As shown in Table 1, there are $5 \times 4 \times 5 = 100$ sets of variable combinations in total, thereby 100 groups of experiments were designed accordingly to figure out the effects of the three variables.

2.3. Experimental Setup

Since the algorithm of cellular automata is stochastic, the results of any one trial have no significance in statistics. Therefore, it is necessary to repeat each group of experiment multiple times. In order to identify the effective number of repeat experiments, a pre-experiment was conducted, which explored the relation between the statistical probability of fire capture (η) and the number of repeat experiments. The camera sight (*R*), the number of cameras in simultaneous operation (*N*), as well as the duration of camera operation (*T*) were fixed to be 25 m, 2, and 100 steps, respectively. The results are presented in Figure 4, in which the symbol η_n means the probability of finding fire within *n* steps. It can be found that as the number of repeat experiments increases, the fluctuation in probability becomes smaller. When the repeat number reaches 500 or more, the probability stabilizes to a constant. That means the probability experiment converges after 500 trials and the

influence of accidental factors can be eliminated. In this case, each group of experiment will be repeated 500 times to obtain reliable statistical results. All experiments involved in this study were implemented on Python 3.8.19.

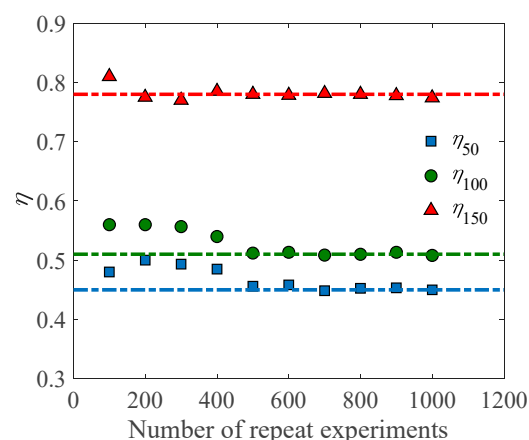


Figure 4. Statistical probability of fire capture versus the number of repeat experiments.

3. Results and Discussion

3.1. Fire Risk

In this section, the statistical probability of fire capture (η) was employed to evaluate the fire risk of the utility tunnel. Different cases were discussed, respectively, as follows according to different configuration of camera sight, covering all possible geometric relations between different monitoring areas.

3.1.1. Cases with Blind Monitoring Area ($R < 25$ m)

The relation between the statistics probability of fire capture and the number of cameras in simultaneous operation for the cases with blind monitoring area ($R < 25$ m) was plotted as in Figure 5. It can be found that in general using cameras with a larger sight can achieve higher probability of fire capture within a shorter time. The probability of finding fire within 50 steps (η_{50}) for cases with a camera sight of 20 m is significantly higher than those with a camera sight of 15 m, regardless of the duration of camera operation (T), while the probability of finding fire within 150 steps (η_{150}) is roughly the same. Both the camera sight of 15 m and 20 m have a rather high probability of finding fire in 150 steps. This indicates that increasing the camera sight is more effective for increasing the probability of finding fire in a shorter period of time. For both cases investigated herein, i.e., Figure 5a,b, the probability of fire capture under the T value of 50 is always the highest among all T values. With the increase in T value, the probability decreases, but the decreasing rate gradually slows down. In this case, higher probability of fire capture can be achieved by reducing the duration of camera operation. Such a measure can have more obvious effects for a longer allowable time and is defined as the value of n in symbol η_n .

As the number of cameras in simultaneous operation increases, the probability of fire capture also increases, but the increasing rate gradually slows down. This is especially obvious at lower T value, which can be attributed to the coupling effect of variables T and N . Both the decrease in T and the increase in N can promote the scanning of the whole tunnel in a shorter period of time, thereby having a higher probability of early fire finding. For cases with lower T value (e.g., $T = 50$), once N has reached a specific value, it is sufficient for the monitoring system to scan the most part of the tunnel within the allowable time by fast alternation of the cameras, and further increase in N contributes little to the probability of fire capture. That is, the effect of variable N is concealed by variable T . But as the T value becomes larger, the cameras alternate slowly, and the monitoring system can hardly scan sufficient area to find the fire early without there being enough cameras in simultaneous operation. In this case, an increase in N value can lead to more

significant increase in the probability. This was confirmed by the curves of large T value in Figure 5 (e.g., $T = 250$), which tend to be linear. The correlation between the probability of fire capture (η) and the number of cameras in simultaneous operation (N) can be described by Equation (1) as the dotted lines in Figure 5 with the fitting goodness (R^2) greater than 0.98, where symbols a , b , and c are all constants.

$$\eta = aN^b + c \quad (1)$$

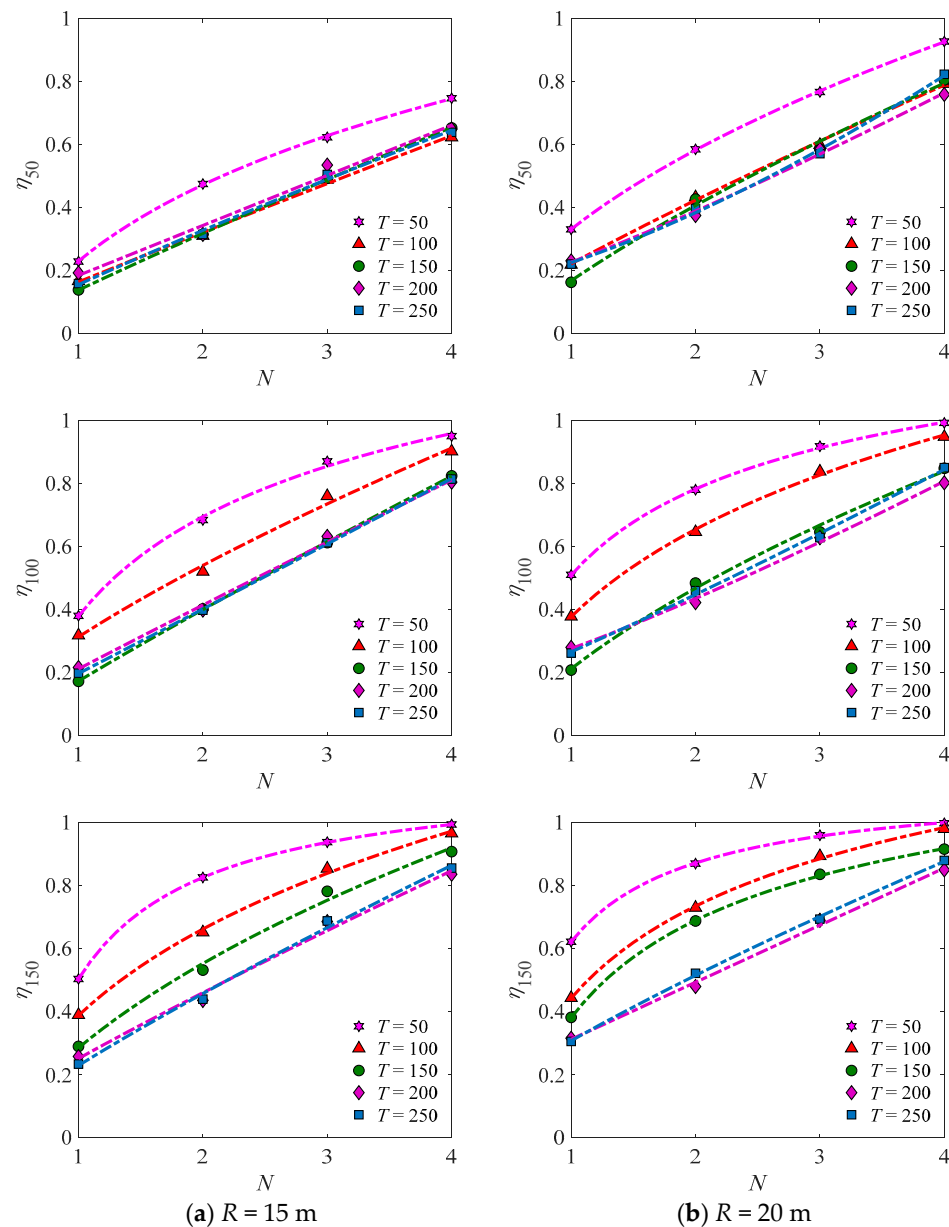


Figure 5. Statistical probability of fire capture versus the number of cameras in simultaneous operation for cases with blind monitoring area ($R < 25$ m).

3.1.2. Cases with Tangent Monitoring Area ($R = 25$ m)

The relation between the statistical probability of fire capture and the number of cameras in simultaneous operation for the cases with tangent monitoring area ($R = 25$ m) is shown in Figure 6. As the number of cameras in simultaneous operation increases, the probability of fire capture also increases, which also satisfies the correlation suggested by Equation (1), as indicated by the dotted lines in Figure 6. Compared with the case with the camera sight of 20 m, the probability of fire capture for the camera sight of 25 m is slightly

higher, but shows no significant difference, especially for those lower T values. Similar to the cases with blind monitoring area ($R < 25$ m), a lower T value can lead to higher probability for fire finding, and the probability under the T value of 50 is still always the highest among all the investigated T values.

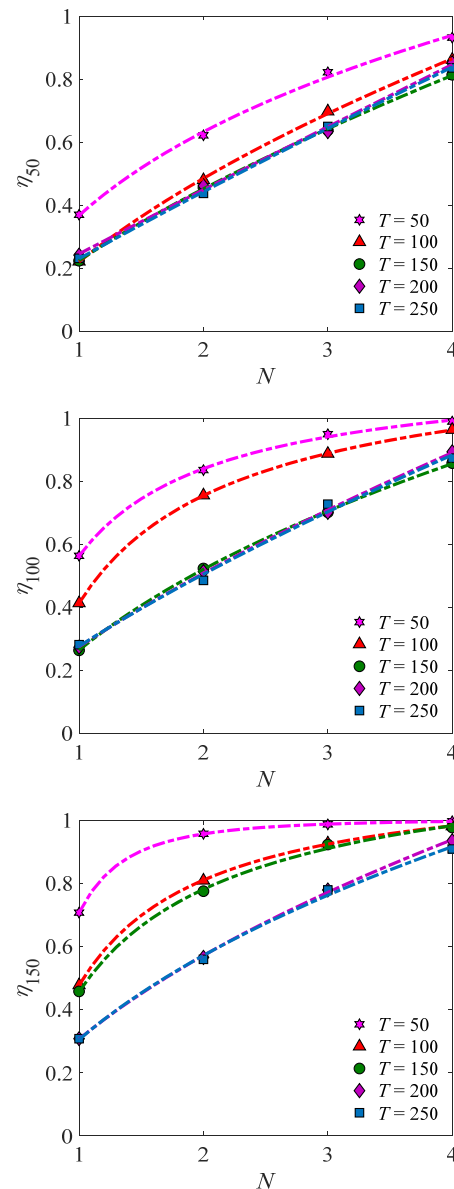


Figure 6. Statistical probability of fire capture versus the number of cameras in simultaneous operation for cases with tangent monitoring area ($R = 25$ m).

An interesting phenomenon can be found that, for the allowable time of 50 steps, the probability of fire capture under the T value of 50 is much higher than that under other T values. While for the allowable time of 100 steps, the probability under the T value of 50 and 100 is much higher than that under other T values. When it comes to the allowable time of 150 steps, the probability under the T value of 50, 100, and 150 is much higher than that under the other two T values. It can be concluded that the probability of fire capture for a T value less than or equal to the allowable time is significantly higher than that for a T value larger than the allowable time. While for a T value greater than the allowable time, the probability is roughly the same, as indicated by Equation (2). Such a phenomenon can also be observed in the cases with blind monitoring area ($R < 25$ m),

which can serve as a criterion for deciding the duration of camera operation (T) considering a given allowable time:

$$\begin{cases} \eta_n(T \leq n) \gg \eta_n(T > n) \\ \eta_n(T_1 > n) \approx \eta_n(T_2 > n) \end{cases} \quad (2)$$

3.1.3. Cases with Overlapping Monitoring Area ($R > 25$ m)

The relation between the statistical probability of fire capture and the number of cameras in simultaneous operation for cases with overlapping monitoring area ($R > 25$ m) is presented in Figure 7, which can still be described with Equation (1) as the dotted lines in the figure show. Compared with the cases with tangent monitoring area ($R = 25$ m), even though the camera sight has increased, the probability does not see much improvement. Only a slight increase in probability could be observed, mainly for the cases with larger T values. Therefore, it is not that efficient to increase the probability of finding fire by continuing to increase the camera sight once there has been no blind monitoring area found.

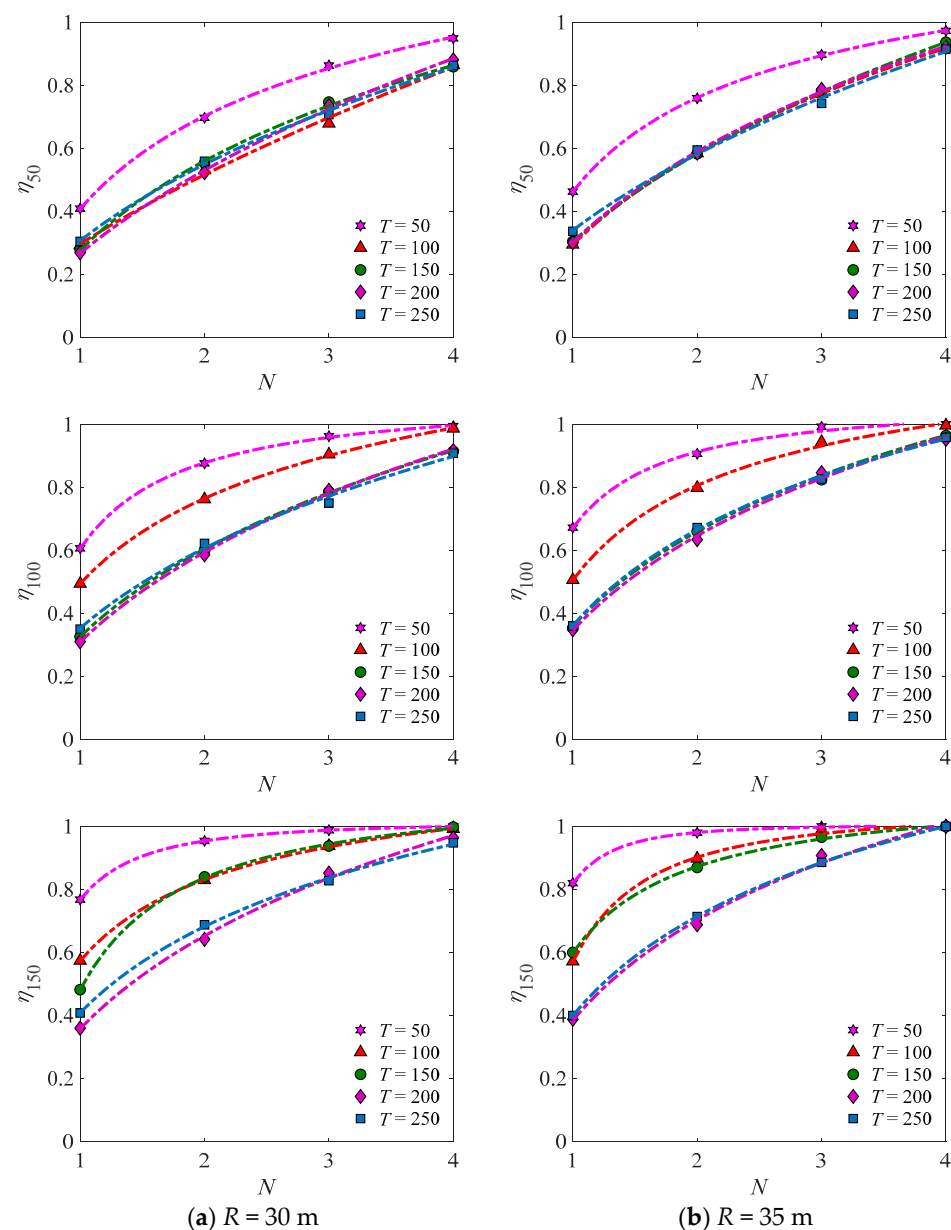


Figure 7. Statistical probability of fire capture versus the number of cameras in simultaneous operation for cases with overlapping monitoring area ($R > 25$ m).

Just like the cases discussed before, with the increase in T value, the probability of fire capture decreases, and the variation still satisfies Equation (2). That means Equation (2) is applicable for all cases regardless of the camera sight. In addition to the law suggested by Equation (2), the probability distribution for the cases with overlapping monitoring area ($R > 25$ m) can be further discussed in more detail. As shown in Figure 7, for the allowable time of 150 steps, the probability under a T value of 50, 100, and 150 is much higher than that under the other two T values. Equation (2) shows indications, based on which the probability curves can be divided into two clusters. One is the cluster containing the curves for the T values of 200 and 250 (Cluster 1), and the other is the cluster containing the curves for the T values of 50, 100, and 150 (Cluster 2). Cluster 2 can be further divided into two clusters since the probability for the T values of 100 and 150 is roughly the same while that for the T value of 50 is much higher. Hence, the probability curves can be divided into three clusters as shown in Equation (3). It should be noted that such division only holds in the cases with an overlapping or tangent monitoring area ($R \geq 25$ m). While for the cases with a blind monitoring area ($R < 25$ m), the difference between the probability for the T value of 100 and 150 is still significant:

$$\eta_{150}(T = 50) \gg \eta_{150}(T = 100) \approx \eta_{150}(T = 150) \gg \eta_{150}(T = 200) \approx \eta_{150}(T = 250) \quad (3)$$

3.2. Energy Consumption

In this section, the energy consumption of different variable combinations was evaluated. The total energy consumption of the monitoring system (E_t) can be simply represented by the product of the average number of steps required for finding fire ($\bar{t}$) and the number of cameras in simultaneous operation (N), as expressed by Equation (4):

$$E_t = N\bar{t} \quad (4)$$

3.2.1. Cases with Blind Monitoring Area ($R < 25$ m)

The variation of the total energy consumption with the duration of camera operation for cases with blind monitoring area ($R < 25$ m) are shown in Figure 8. It can be found that as the T value increases, the total energy consumption also increases, but the increasing rate generally becomes slower. Using one camera each time consumes much more energy than using multiple cameras simultaneously (Equation (5)), and the more of the cameras in simultaneous operation, the lower is the energy consumption. That may be because using more cameras at the same time can find the fire in a much shorter time, in which the time ($\bar{t}$) dominates rather than the number of cameras (N). Meanwhile, although increasing the number of cameras in simultaneous operation can lead to lower energy consumption, the difference is not that significant when the camera number exceeds 1 ($N > 1$). Comparing Figure 8a,b, it can be seen that in general the total energy consumption for the camera sight of 20 m is significantly lower than that for the camera sight of 15 m. That shows reducing the blind monitoring area can effectively save more energy:

$$E_t(N = 1) \gg E_t(N > 1) \quad (5)$$

For the scenarios investigated in this study, the average number of steps required for fire finding ($\bar{t}$) has an upper limit. If the fire could be captured by the monitoring system, it must occur before the burning up of the whole utility tunnel and therefore $\bar{t}$ must be smaller than the number of steps required for the burning of the whole tunnel. Otherwise, it must be smaller than the maximum number of iterations. That means the $E_t - T$ curve would finally converge to a constant. In this case, a model as Equation (6) was established to describe such a correlation, in which symbols a , b , and c are all constants. The fitting curves are shown as dotted lines in Figure 8. It can be seen that even though there is some dispersion in the data points due to the stochastic property of the algorithm, the model generally reflects the trend of the variation, especially for the cases with more cameras in simultaneous operation.

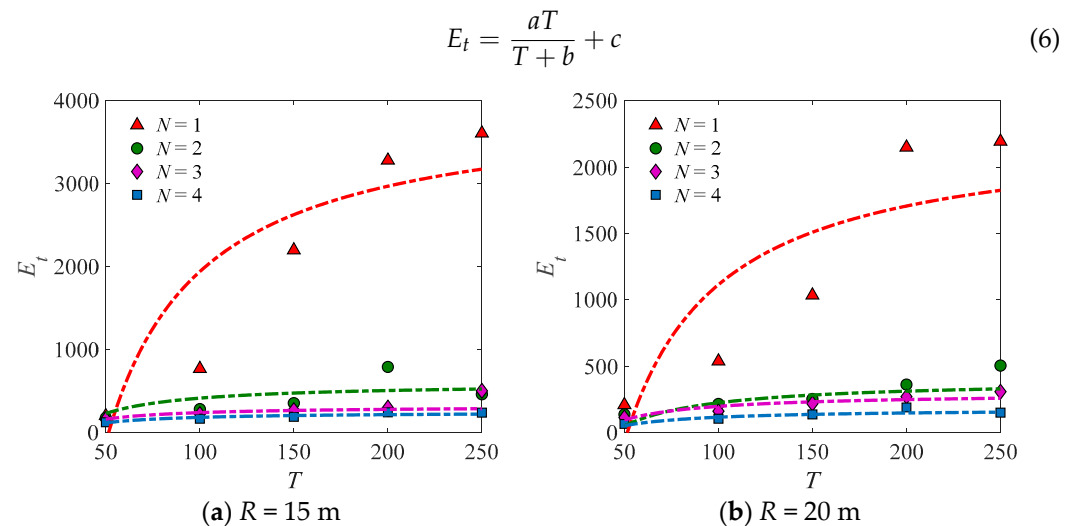


Figure 8. Total energy consumption versus the duration of camera operation for cases with blind monitoring area ($R < 25$ m).

3.2.2. Cases with Tangent Monitoring Area ($R = 25$ m)

The variation of the total energy consumption with the duration of camera operation for cases with tangent monitoring area ($R = 25$ m) are presented in Figure 9. Similar to the cases with blind monitoring area ($R < 25$ m), as the duration of camera operation increases, the total energy consumption also increases, which still satisfies Equation (6). The law indicated by Equation (5) still holds, i.e., the energy consumption of using one camera is much higher than that of using multiple cameras. Compared with the cases with a blind monitoring area ($R < 25$ m), the energy consumption of those with a tangent monitoring area ($R = 25$ m) was generally lower, showing that increasing the camera sight is still effective for lowering the energy consumption.

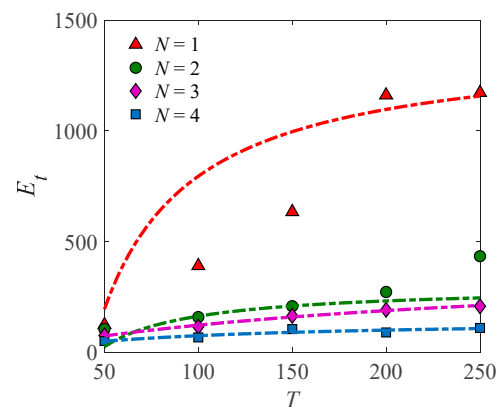


Figure 9. Total energy consumption versus the duration of camera operation for cases with tangent monitoring area ($R = 25$ m).

3.2.3. Cases with Overlapping Monitoring Area ($R > 25$ m)

The variation of the total energy consumption with the duration of camera operation for cases with overlapping monitoring area ($R > 25$ m) is plotted in Figure 10. The features discussed above such as Equation (5) can still be found in Figure 10, and the curves can still be described with Equation (6). Compared with the camera sight of 25 m, the camera sight of 30 m again witnessed a decrease in energy consumption. However, when it increased from 30 m to 35 m, the energy consumption did not show much change. That means increasing the camera sight is only helpful when a blind monitoring area exists. Once the camera sight has increased to form a tangent monitoring area, continuous increase in camera sight will not bring much gain in energy saving.

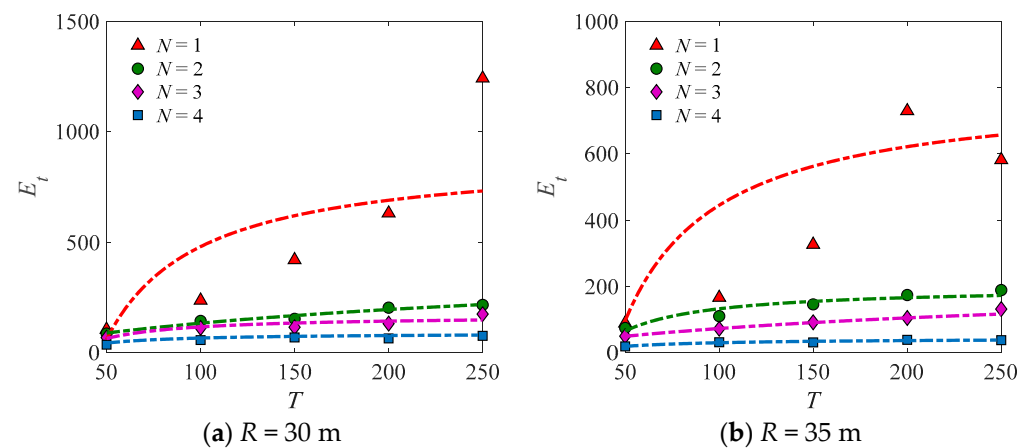


Figure 10. Total energy consumption versus the duration of camera operation for cases with overlapping monitoring area ($R > 25$ m).

3.3. Optimal Design

The optimal values of the design variables are determined as follows.

3.3.1. Number of Cameras in Simultaneous Operation (N)

According to the energy evaluation in Section 3.2, the more of the cameras in simultaneous operation, the lower is the energy consumption. However, since a tunnel fire is an event of small probability and most times there is no fire in a tunnel, using too many cameras in operation can still consume lots of energy. In addition, as suggested by Equation (5), increasing the number of cameras in simultaneous operation can indeed lead to lower energy consumption, but the difference is not that significant when the camera number exceeds one. Therefore, for the sake of energy saving, using two cameras in simultaneous operation seems to be more suitable. Fire risk evaluation in Section 3.1 supports such design as, although using more cameras at the same time can increase the probability of finding fire, a camera number over two will not bring much gain as such for the probability, especially for a T value of 50.

3.3.2. Camera Sight (R)

As discussed in previous sections, increasing the camera sight can significantly increase the probability of fire finding, and meanwhile, lower the total energy consumption. But when there are no more blind monitoring areas, continuous increase in camera sight will not bring much improvement in the two perspectives. Therefore, the camera sight is suggested to be 25 m, i.e., the cases with tangent monitoring area.

3.3.3. Duration of Camera Operation (T)

It was found that increasing the duration of camera operation brings more energy consumption and lowers the probability of fire capture. Therefore, the duration of camera operation should be as short as possible, at least shorter than the allowable time, as suggested by Equation (2).

In summary, the camera number should be first considered, which is the dominant variable in optimization when the camera number is small. But when the camera number exceeds two, the duration of camera operation will become the governing variable in the optimal design. The camera sight generally has relatively less impact on the optimal design, especially when the duration of camera operation as well as the camera number have been optimized.

To show the effectiveness of this study, the optimal design was applied on a utility tunnel in Beijing and compared with its original design [45]. The length of the tunnel is 7.87 km with a total of 353 cameras installed in the monitoring system. With the optimal design proposed in this study, only 197 cameras are required, saving around 44.2% in-

stallation costs. The optimized energy consumption is only 22.3% of the original while maintaining a rather high probability of fire capture within an acceptable allowable time, saving around 24,027 kW·h power each year.

4. Conclusions

In this paper, a utility tunnel section with five cameras was investigated. A cellular automata-based algorithm was used to simulate the spread of fire in the utility tunnel. Three design variables including the camera sight (R), the number of cameras in simultaneous operation (N), and the duration of camera operation (T) were optimized considering both fire risk and energy consumption. The effects of the three variables were revealed, and the optimal design strategy for a camera-based fire monitoring system was proposed. The conclusions are summarized as follows.

- (1) As the number of cameras in simultaneous operation increases, the probability of fire capture also increases, but the increasing rate gradually slows down, which is especially obvious for the cases with lower T values. Such a correlation can be well described with a power model. A lower T value can lead to higher probability of fire capture, and the probability of fire capture for a T value less than or equal to the allowable time is significantly higher than that for a T value larger than the allowable time. While for a T value greater than the allowable time, the probability is roughly the same. Increasing the camera sight can increase the probability of fire finding. But when there is no blind monitoring area, continuous increase in camera sight contributes little to the increase of the probability.
- (2) As the duration of camera operation increases, the total energy consumption of the monitoring system also increases, and the relation can be described with a hyperbolic model. Using one camera at a time consumes much more energy than using multiple cameras simultaneously, and the more of the cameras in simultaneous operation, the lower is the energy consumption. However, when the number of cameras in simultaneous operation exceeds one ($N > 1$), the difference in total energy consumption is not that significant. Increasing the camera sight can effectively reduce the total energy consumption when a blind monitoring area exists. But once the camera sight has increased to form a tangent monitoring area, continuous increase in camera sight will not save more energy.
- (3) The optimal design for the discussed case is suggested to be two cameras in simultaneous operation with a camera sight of 25 m (i.e., a tangent monitoring area). The duration of camera operation should be as short as possible, at least shorter than the allowable time.

The conclusions can be directly applied in utility tunnels with no or little modification, and can be easily achieved in fire monitoring systems through computers automatically. However, it should be clarified that there are also some limitations. For instance, the cellular automata algorithm is only a simplification of real fire propagation and cannot simulate more complex fire scenarios, and the findings may not be applicable to tunnels with a large curvature. This study aims to provide a basic reference for the design of more sustainable utility tunnels with lower fire risk.

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