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Article

Playing Chemical Plant Environmental Protection Games with Historical Monitoring Data

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Abstract: The chemical industry is an integral part of the world economy and a substantial income source for developing countries. However, existing regulations or the enforcement of these regulations, on controlling atmospheric pollutants sometimes may be insufficient, leading to the deterioration of surrounding ecosystems and to a quality decrease of the atmospheric environment. Previous works in this domain fail to generate executable solutions for inspection agencies due to practical challenges. In addressing these challenges, we introduce a so-called Chemical Plant Environment Protection Game (CPEP) to generate reasonable schedules of high-accuracy air quality monitoring stations for inspection agencies. First, Stackelberg Security Games (SSGs) are incorporated together with source estimation methods into this research. Second, high-accuracy air quality monitoring stations as well as gas sensors are modeled into the CPEP. Third, simplified data analysis on the regularly discharging of chemical plants is utilized to construct the CPEP. Finally, an illustrative case study is used to investigate the effectiveness of the CPEP Game, and a realistic case study is conducted to illustrate how the models and algorithms being proposed in this paper, work. Results show that playing a CPEP Game can reduce operational costs of high-accuracy air quality monitoring stations; moreover, playing the game leads to more compliance from the chemical plants towards the inspection agencies.

Keywords: chemical plant environmental protection; stackelberg security games; source estimation methods; historical monitoring data; game theory

1. Introduction

Controlling atmospheric pollution is substantial and urgent in the situation of today's atmospheric environment. Chemical industrial activities are an important factor leading to the deterioration of the atmospheric environment. Nonetheless, the chemical industry's role in the global economy cannot be underestimated, and especially in developing countries, for instance in China and in India, this is the case. Unfortunately, the byproducts generated during production processes are noxious, even sometimes highly toxic, and often they are discharged to the nearby atmospheric environment without purification treatment. As a result, the atmospheric quality in these countries is extremely poor [1], leading to substantial health problems for the residents and to the destruction of the ecosystem. Recent results (e.g., [2]) indicate that atmospheric pollution can cause cardiovascular system diseases, respiratory system diseases, lung cancer and other related diseases.

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Faced with these problems, governments in developing countries have introduced a series of measures to abate atmospheric pollution [3,4]. For instance, chemical plants are required by law to dispose atmospheric pollutants through Purification Treatment Plants (PTPs) prior to releasing them into the air. However, the chemical plants do not run PTPs in most instances, in order to earn more profits. It is often up to regulatory bodies or inspection agencies to enforce compliance by fining these chemical plants in case that violation behavior of chemical plants is detected. However, on the one hand, many inspection agencies lack in inspecting resources; and on the other hand, it is difficult for them to draw up an intelligent strategy to detect these irregularities. Thus, one of the most simple and rude methods is banning these factories, which may solve the problem in a short term, but the downside is that such a measure would do substantial harm to national economies.

Previous work in addressing this non-compliance issue falls short of generating effective solutions for inspection agencies to optimize the audit and detection. With the help of the government, the inspection agency is nonetheless equipped with atmospheric monitoring facilities to conduct air monitoring. However, without utilization of source estimation methods, it is still hard for inspection agencies to distinguish whether a factory violates or not. Besides, inspection agencies do not dispose of quantitative and effective methods to conduct their inspection schedules. Therefore, inspection agencies are having difficulties in dealing with this problem at present.

With recent developments and successful deployments in various domains, such as seaports, airports, airline flights and rapid transit systems [5,6], game-theoretic models are able to provide a rigorous and mathematically based method to quantitatively model the interaction between the inspection agency and the chemical plants.

Game-theoretic models, especially Stackelberg Security Games (SSGs) are utilized in earlier studies to generate intelligent security strategies. A generic Stackelberg Game consists of two players [7], a leader (a defender) and a follower (an attacker), in which a defender attempts to optimally allocate her limited security resources to protect a set of targets against an adversary attempting to attack one of the targets to optimize his utility. In SSGs, the defender commits to a mixed strategy first while the follower can observe the mixed strategy and subsequently take an action to optimize his reward. A pure strategy of the defender is an assignment of her limited resources to a subset of targets and a mixed strategy of the defender refers to a probability distribution over all possible pure strategies [8]. A marginal coverage vector over the targets is often used to represent mixed strategies of the defender (i.e., the coverage probability with which the defender will protect each target) [9]. The number of targets demanding protection and the defender's coverage probability at target i can be denoted by N and c_i respectively ($0 \le c_i \le 1$, $i = 1...N$). When the adversary attacks a target i, he will receive a reward R_i^a if the target is not protected by the defender's resource; otherwise, he will receive a penalty P_i^a. Conversely, the defender will get a penalty P_i^d in the former case and a reward R_i^d in the latter case. The expected payoff of the defender, U_i^d, and attacker, U_i^a, are computed as follows.

$$U_i^d = c_i \cdot R_i^d + (1 - c_i) \cdot P_i^d, \tag{1}$$

$$U_i^a = c_i \cdot P_i^a + (1 - c_i) \cdot R_i^a, \tag{2}$$

Inspired by the success of applying defender-attacker SSGs in protecting infrastructure including airports, ports and trains, SSGs have been applied in domains of chemical plant protection and environment protection with two orientations: Chemical Plant Protection Games (CPPs) and Green Stackelberg Games (GSGs). In the chemical security domain, a game theoretic approach was utilized by Reniers et al. [10-15] to systematically study cooperation regarding safety and security investments within chemical clusters. Whether investing in safety and security, or not, by the stakeholders of plants is the main focus in their model. Then, Zhang and Reniers [16] introduced a simultaneous game-theoretic model called "CPP Game" to protect chemical plants from terrorist attacks, and later on they [17] extended their model to sequential games played by a

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leading defender and several types of following attackers. These initial successes pointed the way to major future applications in the CPP security domain, with major challenges in scaling up game-theoretic algorithms, to addressing bounded rationality of human adversaries and uncertainties in action execution and observation. Besides, GSGs also emerged up in recent years, applications of which mainly focused on protecting the environment, including forests, fish and wildlife [18]. One of the newer applications in this field was protecting forests [19], where spatial considerations are taken into enforcement decisions for the defender. Another area of interest was protecting endangered species, in which PAWS (Protection Assistant for Wildlife Security) [20] is a typical application. Additionally, an emerging application domain was that of ensuring the sustainability of fish resources [21,22]. In our work, the atmospheric pollutants prevention problem is different from the two domains of applying SSGs mentioned above. Our research goal is to protect the environment and reduce operational costs of inspecting resources while CPPs are proposed to protect important properties and facilities from attacks. Moreover, GSGs, the concept of which is repeated SSGs, have not paid any attention to the issue of protecting atmospheric environment yet. The essence of GSGs is the models which are used to deal with adversaries who are characterized by bounded rationality. However, violation data of discharging excessive atmospheric pollutants are absent in this research to learn the behavioral model of the adversaries. Therefore, our Chemical Plant Environment Protection Games (CPEPs), different from the general concept of GSGs, follow the way of basic SSGs.

We introduce a new game-theoretic model named CPEPs because of successful applications in related domains. In the background of a chemical industrial park, chemical plants tend to maximize their profits by discharging excessive atmospheric pollutants without purification treatment, while an inspection agency is charged with the work to inspect the production process of chemical plants. Once irregularities of the chemical plants are caught by the inspection agency, the chemical plants will be heavily fined. In this paper, CPEPs focus on generating an optimal defender strategy against a one-shot defender-attacker interaction to reduce costs and control pollution.

The remainder of this paper is organized as follows: Section 2 presents the main modeling process of CPEPs with corresponding solving algorithms. Case studies are conducted in Section 3 to illustrate how the models and algorithms being proposed in this paper, work. Finally, conclusions and future lines of research are discussed in Section 4. Table 1 lists key notations used in this paper.

Table 1. Key notations used in this paper.

Notation	Explanation
N	Number of chemical plants
γ_1	Probability of detecting violation behavior without monitoring stations
γ_2	Probability of detecting violation behavior with opening monitoring stations
C_d	Operational costs of monitoring stations in the time unit for defender
C_a	Operational costs of Purification Treatment Plant in the time unit for attacker
R_l^a	Reward of the lth attacker discharging atmospheric pollutants but defender fails to detect the violation behavior for attacker
P_l^d	Penalty of the lth attacker discharging atmospheric pollutants but defender fails to detect the violation behavior for defender
P_l^a	Penalty of the lth attacker discharging atmospheric pollutants but defender successfully detects the violation behavior for attacker
R_l^d	Reward of the lth attacker discharging atmospheric pollutants but defender successfully detects the violation behavior for defender
u_d	Payoffs in one game against N attackers for defender
u_a^l	Payoffs in one game against defender for the lth attacker
P^l	Probability of the lth attacker occurrence
T	Time slices in a day

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2. Model Description

In this section, CPEPs are built up in subsection 2.1 and some definitions will be given at the same time. Source estimation methods are briefly introduced in subsection 2.1.3. Finally, baseline algorithms are introduced in subsection 2.2 to deal with CPEPs.

2.1. CPEP model

The game-theoretic model, which we need to develop, should provide an approach to deal with interactions between the intelligent adversary, that are the chemical plants ('attackers') and the inspection agency ('defenders'). The model should assist the inspection agency to carry out their audit and detection approach in a more efficient and effective way. Basically, if an inspection agency in a chemical industrial park is equipped with high-accuracy air quality monitoring stations and gas sensors, these inspection resources would be operated continuously (24/7), regardless of the cost, in present practice. Different from the present practice, we model this atmospheric pollution prevention problem as a defender-attacker Stackelberg Security Game. Generally, strategic players are included in a game theoretic model. Each player has a set of feasible actions or choices, which are called pure strategies in the game theoretic terminology. After these strategies are conducted, players will acquire a reward or receive a penalty correspondingly. Payoffs can be calculated accordingly (e.g., by formulas (1) and (2)). Finally, solutions constituted of typical strategies are discussed in subsection 2.1.4. The elements mentioned above are modeled step by step in CPEPs as explained hereafter.

2.1.1. Players

In our research problem at hand, the defender is the inspection agency and the attackers are the chemical plants, where the attackers attempt to discharge excessive atmospheric pollutants to optimize their payoffs after observing the action taken by the defender (we use "leader" or "defender" to refer to the inspection agency and "follower" or "attacker" to refer to the chemical plant in the remainder of this paper). The task of the defender is to optimize the operating schedules of high-accuracy air quality monitoring stations to achieve more compliance from the chemical plants, and at the same time, to reduce its operational costs. Moreover, both the chemical plants and the inspection agency are assumed rational based on two basic reasons in this paper. First, both players in CPEPs are able to perceive their situation and the opposite player's actions accurately. The second reason is that they tend to maximize their payoff through intelligently planning their strategies. Meanwhile, the interactions between the inspection agency and the chemical plants are characterized by the following considerations: (i) Knowledge about the capabilities and locations of the high-accuracy air quality monitoring stations and gas sensors is available to the chemical plants, primarily from the long-term observation of these facilities. (ii) Basic knowledge about the chemical plants, for instance, the locations, main productions, byproducts and etc. is available to the inspection agency, since this is information that needs to be provided by the chemical plants. (iii) Knowledge about pure strategies of players is available to both parties.

In this article, we use Θ to represent the inspection agency and Ψ to refer to the chemical plant.

2.1.2. Strategies

The pure strategy of players within the context of a chemical industrial park is a binary choice (i.e., for the inspection agency, open the monitoring stations or close the monitoring stations; for the chemical plants, release the excessive atmospheric pollutants or not) in different time slices in one day. One day is assumed to be equally divided into T time slices and the defender is assumed to have R monitoring stations (i.e., R high-accuracy inspection resources). But in practice, though the defender might have multiple monitoring stations, she operates these resources on the same states (e.g., in one time slice, turn on or turn off all the stations). Therefore, these inspection

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resources can be considered to be one resource. An explanation of this operation is given in the case study section. Besides, we use S_Θ and S_Ψ to denote an index set of pure strategies for the inspection agency and the chemical plants respectively. Thus, the pure strategy set of the inspection agency can be denoted as $\Sigma_\Theta = \{\theta_1, ..., \theta_{|S_\Theta|}\}$ while $\Sigma_\Psi = \{\psi_1, ..., \psi_{|S_\Psi|}\}$ is the pure strategies set for the attacker. The formulated representations of θ_i, ψ_i, $|S_\Theta|$ and $|S_\Psi|$ are exhibited in the following formulas.

$$\theta_i = \Pi_{r\in|R|, t\in|T} \, s_d(r,t), \tag{3}$$

$$\psi_i = \Pi_{t\in|T|} \, s_a(t), \tag{4}$$

$$|S_\Theta| = 2^{R\cdot T}, \tag{5}$$

$$|S_\Psi| = 2^{T}, \tag{6}$$

Where θ_i represents a pure strategy for the defender while ψ_i denotes a pure strategy for the attacker; the notation of $|R|$ denotes $|R| = \{1, 2, ..., R\}$; similarly, the parameter of $|T|$ means $|T| = \{1, 2, ..., T\}$; the notation of $s_d(r,t)$ means $s_d(r,t) \in \{open, close\}$ while the notation of $s_a(t)$ means $s_a(t) \in \{release, no\ release\}$; the cross product is denoted through Π; the number of pure strategies for the inspection agency and the chemical plant is denoted through $|S_\Theta|$ and $|S_\Psi|$ respectively.

According to formula (3), a pure strategy of the defender is defined as a combination of operation states of monitoring stations in all time slices in a day. Similarly, a pure strategy of the attacker is defined as a combination of discharging states in all time slices in a day according to formula (4). For instance, if time slices T in one day are set at two and the value of R is set at one, the pure strategies for both players in one day are shown in Table 2. At the same time, a mixed strategy refers to a probability distribution over all possible pure strategies. For the defender, we use $x_i \in [0,1]$ to indicate the probability of the defender utilizing the pure strategy $\theta_i \in \Sigma_\Theta$. In contrast, the chemical plant takes action after observing the inspection agency's mixed strategy and he will choose the best strategy to response rather than mix his strategy, to this end, $q_i \in \{0,1\}$ is used to indicate the probability of the attacker utilizing the pure strategy $\psi_i \in \Sigma_\Psi$.

Table 2. Pure strategy of defender and attacker in one day with two time slices.

Notation	Defender's Strategy	Notation	Attacker's Strategy
θ_1	$\{open, open\}$	ψ_1	$\{release, release\}$
θ_2	$\{open, close\}$	ψ_2	$\{release, no\ release\}$
θ_3	$\{close, open\}$	ψ_3	$\{no\ release, release\}$
θ_4	$\{close, close\}$	ψ_4	$\{no\ release, no\ release\}$

The division of one day determines how many pure strategies that the inspection agency and the chemical plants will have. A method based on historical discharging data is proposed in this paper to divide one day. Here, a figure of a daily hour-average concentration trend detected by high-accuracy air quality monitoring stations during the past year is shown as below. In Fig.1, the *X*-axis is the time series of one day while the *Y*-axis represents the main atmospheric contaminants monitored by monitoring stations. There are about 118 types of main atmospheric pollutants (e.g., Nitrogen oxides, Carbon oxides, VOCs and etc.) studied in this paper. The background color of this figure is white, which means concentration value of atmospheric pollutants is zero. Furthermore, a darker area represents higher gas concentration in this figure. It can be concluded from the

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color-bar that black is darker than grey and white means that the concentration of the former is greater than that of the latter. From the figure, it is obvious that discharging behavior of chemical plants clearly has time characteristics. The discharging amount of atmospheric pollutants in the time unit of 12-24 hours is far greater than that in the time unit of 1-12 hours. Basically, production processes within chemical plants last for several hours. Hence, it is impractical to divide the time segment narrowly. Moreover, high-accuracy air quality monitoring stations are unsuitable to open and close frequently because a high start-up frequency may damage the facilities [23]. Therefore it is reasonable to divide one day into two time slices in this paper.

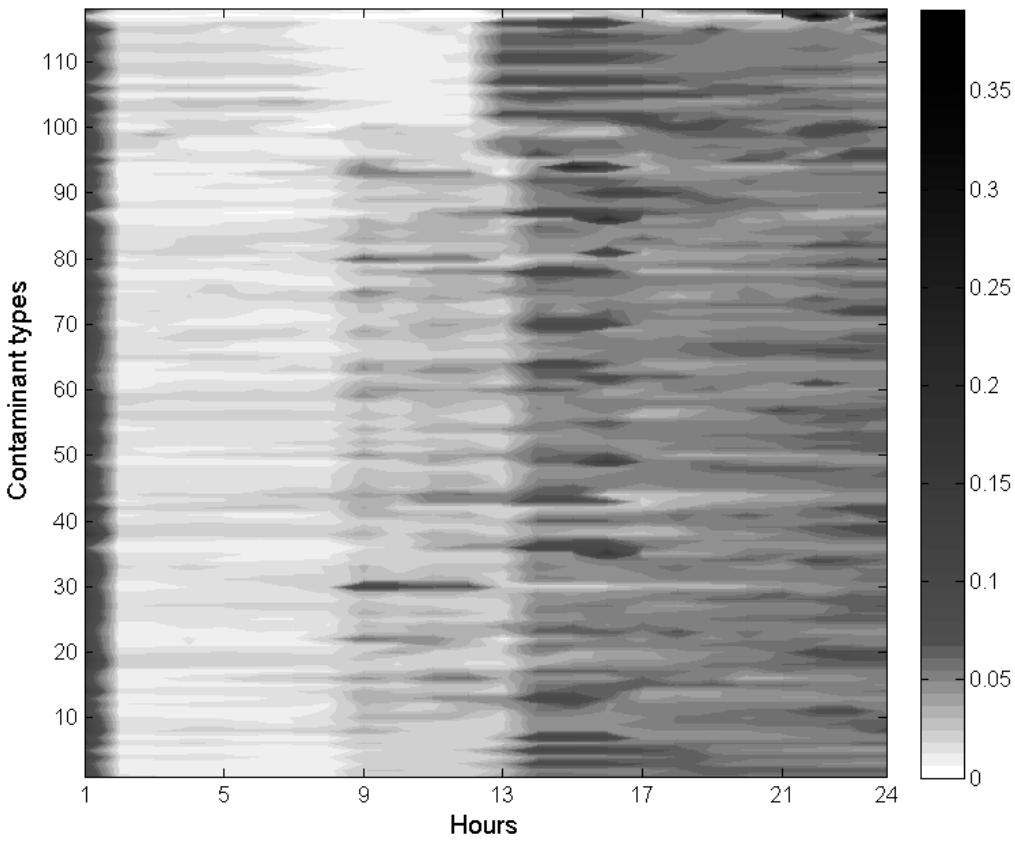

Figure 1. Daily hour-average concentration trend during the past year.

This paper only offers a choice for readers to apply historical data into the modeling process. Interested readers can propose other reasonable approaches when determining the value of time slices in one day. Since the number of pure strategies is exponential to the value of T, a narrow division of one day will lead to high computation challenges. To simplify the modeling process and to ensure the safety of facilities, the value of T has an upper bound in most instances.

2.1.3. Payoffs

In this subsection, source estimation methods are modeled into CPEPs to predict the violation behavior of the chemical plants. The ability of source estimation methods successfully predicting the irregularities of chemical plants with only the discharging data from the gas sensors is defined as γ_1 while that with the discharging data from the fusion data of monitoring stations and gas sensors is defined as γ_2. The probability of γ_2 is assumed to be larger than that of γ_1 because monitoring data collected by high-accuracy air quality monitoring stations is more helpful in predicting the potential releasing spots. The source consists of two indicators: one is the location of the releasing spot and the other is the releasing rate of the discharging spot. After the potential

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releasing spots are calculated through source estimation methods when real-time monitoring data are applied as inputs, the inspection agency will send a law enforcement team to verify the violation behavior.

The parameters explained hereafter are also determined to calculate the payoff of both defender and attacker from the point of view of the inspection agency. There are N chemical plants in a chemical industrial park and several high-accuracy air quality monitoring stations conducting surveillance. Other than high-accuracy air quality monitoring stations, an inspection agency is also assumed to have deployed a large number of portable gas sensors spread all over the chemical industrial park. Therefore, the inspection agency has a certain possibility to distinguish whether a factory is discharging atmospheric pollutants in the circumstance even if high-accuracy air quality monitoring stations are shut down. The operation cost of high-accuracy air quality monitoring stations in a time unit for the inspection agency is defined as C_d while the operation of a purification treatment plant for treating atmospheric pollutants in a time unit for a chemical plant is C_a. Commonly, the operation cost of PTPs is much higher than that of high-accuracy air quality monitoring stations. If the lth chemical plant discharges atmospheric pollutants and the inspection agency fails to detect the violation behavior, the chemical plant obtains a reward R_l^a while the inspection agency gets a penalty P_l^d; conversely, if the inspection agency successfully detects the violation behavior, the chemical plant receives a penalty P_l^a while the inspection agency achieves a reward R_l^d. In developing countries (e.g. China and India), the government has published detailed regulations that if a chemical plant is caught of discharging excessive pollutants, it will be fined heavily. Part of the fine will be served as a reward for the work of the inspection agency. Thereby, it is assumed that $0 \le -P_l^d \le R_l^d$ and $0 \le R_l^a \le -P_l^a$. Primarily, the reward R_l^a comes from discharging excessive atmospheric pollutants without purification treatment while the penalty P_l^d comes from the pressure of public opinion and authorities. In addition, both the penalty P_l^a and the reward R_l^d come from forfeit.

The binary choice for the inspection agency (e.g., only one inspection resource is considered) and the chemical plant in one time slice constructs a payoff matrix, where the chemical plant is the row player while the inspection agency is the column player. Thus payoff tuples can be represented as (u_a, u_d) in Table 3. The payoff matrix can also be considered as payoffs in the circumstance of pure strategy for the inspection agency and the chemical plant when the value of T is set at one.

Table 3. Payoff matrix in a time slice with only one defender and one attacker.

Attacker \ Defender	Open	Close
Release	$(1-\gamma_2)\cdot R_l^a + \gamma_2 \cdot P_l^a, \gamma_2 \cdot R_l^d + (1-\gamma_2)\cdot P_l^d - C_d$	$(1-\gamma_1)\cdot R_l^a + \gamma_1 \cdot P_l^a, \gamma_1 \cdot R_l^d + (1-\gamma_1)\cdot P_l^d$
No release	$-C_a, -C_d$	$-C_a, 0$

In the first case, when the high-accuracy air quality monitoring stations are open and the chemical plant is releasing excessive atmospheric pollutants, the payoff for the inspection agency is computed as the reward of a successful detection by high-accuracy air quality monitoring stations and gas sensors plus the penalty of unsuccessful detection by the inspection minus the operational costs of the high-accuracy air quality monitoring stations through the formula $\gamma_2 \cdot R_l^d + (1-\gamma_2)\cdot P_l^d - C_d$. Similarly, the difference in the second circumstance is the shutting down of the high-accuracy air quality monitoring stations compared to the first case, and thus the corresponding payoff for the inspection agency is calculated by the reward of successful detection by gas sensors plus the penalty of unsuccessful detection through the formula $\gamma_1 \cdot R_l^d + (1-\gamma_1)\cdot P_l^d$. The payoffs for the inspection agency are quite easy in the third and fourth cases, denoted as C_d

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and 0 respectively. Analogously, in the first circumstance, the payoff for the chemical plant is computed as the reward of successfully discharging excessive atmospheric pollutants plus the penalty of unsuccessful violation under the probability γ_2 through the formula $(1-\gamma_2)\cdot R_l^a+\gamma_2\cdot P_l^a$. The difference for the chemical plant to compute his payoff in the second case is the probability, denoted as γ_1 compared to the first circumstance. The payoffs for the chemical plant are simple in the third and fourth cases, both denoted as C_a.

Then, the parameters p_{a1}, p_{a2}, p_{a3} and p_{a4} are used to represent the payoffs for the chemical plant under the pure strategy tuple of $(release, open)$, $(release, close)$, $(no\ release, open)$ and $(no\ release, close)$ respectively; similarly, the parameters p_{d1}, p_{d2}, p_{d3} and p_{d4} are used to represent the payoffs for the inspection agency under the pure strategy tuples mentioned above. Based on these parameters, the payoffs for both players under pure strategy tuple of (θ_i, ψ_j) in T time slices are exhibited in the following formulas.

$$u_d^l(\theta_i,\psi_j)=\sum_{k=1}^{4}N_k\cdot p_{dk}\,, \tag{7}$$

$$u_a^l(\theta_i,\psi_j)=\sum_{k=1}^{4}N_k\cdot p_{ak}\,, \tag{8}$$

$$\sum_{k=1}^{4}N_k=2^{T\cdot(R+1)}\ \forall N_k\in[0,2^{T\cdot(R+1)}]\ and\ N_k\in Z\,, \tag{9}$$

Where the notation of N_k denotes the number of the kth pure strategy tuples (i.e., $(release, open)$, $(release, close)$, $(no\ release, open)$ and $(no\ release, close)$) under the pure strategy tuple of (θ_i, ψ_j) in T time slices. Formulas (7) and (8) represent calculating the summation of each product, that is, the multiplication of the the number of the kth pure strategy tuples with the corresponding payoff.

Moreover, in view of the above formulas and Table 3, the payoffs for the inspection agency and the chemical plant in the circumstance of mixed strategy can be shown as follows:

$$u_d^l(x,q)=\sum_{i\in S_\Theta}\sum_{j\in S_\Psi}u_d^l(\theta_i,\psi_j)\cdot x_i\cdot q_j^l\,, \tag{10}$$

$$u_a^l(x,q)=\sum_{i\in S_\Theta}\sum_{j\in S_\Psi}u_a^l(\theta_i,\psi_j)\cdot x_i\cdot q_j^l\,, \tag{11}$$

In a one-shot game, when the chemical plants are expanded to many types, the payoff for the inspection agency is converted to formula (12).

$$u_d(x,q^1,\ldots,q^N)=\sum_l p^l\cdot u_d^l(x,q^l)=\sum_l p^l\cdot\sum_{i\in S_\Theta}\sum_{j\in S_\Psi}u_d^l(\theta_i,\psi_j)\cdot x_i\cdot q_j^l\,, \tag{12}$$

Where $q^l\ (l=1,\ldots,N)$ defines the probability distribution vector over the l_{th} attacker's strategy; and p^l indicates the probability that the l_{th} attacker occur.

Finally, based on formulas (11) and (12), when a set of reasonable values for the parameters in Table 1 is determined, solutions can be computed through the baseline algorithms in subsection 2.2.

2.1.4. Solutions concepts of the CPEP Game

Although the use of simultaneous games in the security domain is still common [16,24,25] in current game-theoretic model, three reasons are proposed in this paper to enforce us to prefer modeling our CPEPs as sequential games.

Firstly, playing sequentially can reflect the industrial practice in a chemical industrial park better. In this paper, it is often the case that the inspection agency commits to her strategy first, and then the chemical plants intelligently plan their violation schedules after observation. That is to say, the chemical plants not only are able to collect information about the chemical industrial park, but they can also gather information about the inspection agency's strategies. Therefore, it is reasonable to assume that the attackers have both complete and perfect information of a sequential game [26].

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Secondly, playing sequentially can bring a higher payoff to the inspection agency. In SSGs, if the defender is permitted to implement her mixed strategy first, she will acquire the so-called "First-mover Advantage" [27]. Moreover, Letchford [27] proved that the payoff of the defender from the mixed strategy is no less than that from simultaneous move. Based on the "First-mover Advantage", the inspection agency could choose to play a mixed strategy and then make her strategy public to enforce the game being a sequential game which is beneficial to her.

Thirdly, playing sequentially can avoid the problem of equilibria selection. The Nash Equilibrium [28] is the most common solution concept computing the outcome in a simultaneous game. Since our CPEPs are not zero-sum games, it is possible to have multiple NE solutions [29]. Playing sequentially can make our CPEP game predictable and controllable for the inspection agency because the Strong Stackelberg Equilibrium (SSE) proposed by Leitmann [30] can ensure a unique solution in sequential games. Furthermore, Von Stengel and Zamir [31] introduced the ideal theory that the defender can choose the strategy which is close to the equilibrium solution, so that the attackers tend to choose a strategy which is beneficial to the defender, so as to achieve the SSE.

In addition, chemical plants can be expanded into many types because their main products are different, leading to different payoffs for the chemical pants and the inspection agency. In this situation, our CPEPs are evolved into Bayesian Stackelberg Security Games which are the most common framework for reasoning about uncertainties accounting payoffs of attackers. Besides, the aim of the inspection agency is choosing a mixed strategy to maximize her payoff when best responses of all types of the chemical plants are considered. We name the best solution in this situation as the Bayesian Stackelberg Equilibrium (BSE) [32]. Therefore, the SSE solution and the BSE solution are defined as the solution concepts in this paper rather than the NE solution.

2.2. Baseline algorithm to solve the CPEP Game

There are two baseline algorithms utilized in this paper: the MultiLPs (Multiple Linear Programmings) algorithm and the DOBSS (Decomposed Optimal Bayesian Stackelberg Solver) algorithm. The MultiLPs algorithm was firstly proposed by Contizer and Sandhol [32], which is utilized to deal with CPEPs in the case that the game between the inspection agency and a certain type of chemical plant is computed. Interested readers are referred to Contizer and Sandhol [32].

As background information about CPEPs, the number of pure strategies for the attackers is growing exponentially as the types of attackers enlarge in the Harsanyi transformation [33] if MultiLPs algorithm is used to solve the problem. In fact, the independence among the attackers could be modeled to design a new algorithm to solve this problem. DOBSS, the currently most efficient general Stackelberg solver [34], is applied for security scheduling at the Los Angeles International Airport which operates directly on the compact Bayesian representation. The key to the DOBSS decomposition is the observation that evaluating the defender strategy against a Harsanyi-transformed game matrix is equivalent to evaluating against each of the game matrices for the individual attacker types and then obtaining a weighted sum. Given prior probabilities p_l for the chemical plants, the inspection agency solves the following problem formulation:

$$\max_{x,q,a} \ \sum_{i\in S_\Theta} \sum_{l\in N} \sum_{j\in S_\Psi} p^l \cdot u_d^l(\theta_i, \psi_j) \cdot z_{ij}^l , \tag{13}$$

$$s.t. \quad \sum_{i\in S_\Theta} \sum_{j\in S_\Psi} z_{ij}^l = 1 \ \ \forall l \in N , \tag{14}$$

$$\sum_{j\in S_\Psi} z_{ij}^l \le 1 \ \ \forall l \in N, i \in S_\Theta , \tag{15}$$

$$q_j^l \le \sum_{i\in S_\Theta} z_{ij}^l \le 1 \ \ \forall l \in N, j \in S_\Psi , \tag{16}$$

$$\sum_{j\in S_\Psi} q_j^l = 1 \ \ \forall l \in N , \tag{17}$$

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$$0 \le (a^l - \sum_{i \in S_\Theta} u_a^l(\theta_i, \psi_j) \cdot (\sum_{h \in S_\Psi} z_{ih}^l)) \le (1 - q_j^l) \cdot M \quad \forall l \in N, j \in S_\Psi, \tag{18}$$

$$\sum_{j \in S_\Psi} z_{ij}^l = \sum_{j \in S_\Psi} z_{ij}^1 = \sum_{j \in S_\Psi} z_{ij}^2 = \ldots = \sum_{j \in S_\Psi} z_{ij}^N \quad \forall l \in N, i \in S_\Theta, \tag{19}$$

$$z_{ij}^l \in [0,1] \quad \forall l \in N, i \in S_\Theta, j \in S_\Psi, \tag{20}$$

$$q_j^l \in \{0,1\} \quad \forall l \in N, j \in S_\Psi, \tag{21}$$

$$a^l \in \Re \quad \forall l \in N \tag{22}$$

Where M is a large positive number; the variable of a^l is set to the maximum reward the l_{th} attacker can receive, given the current policy of x taken by the defender; the notation of $z^l{}_{ij}$ represents $z^l{}_{ij} = x_i \cdot q^l{}_j$. The two inequalities in constraint five ensure that $q^l{}_j = 1$ only for a strategy j that is optimal for follower type l. The constraint five can be explained in detail as follows: the leftmost inequality indicates that given the defender's policy x, a^l is the upper bound of the l_{th} attacker's utility for any strategy. While the rightmost inequality is inactive when $q^l{}_j = 0$ because M is a large positive quantity. For the strategy that has $q^l{}_j = 1$, the rightmost inequality can be transformed into $a^l \le \sum_{i \in S_\Theta} u_a^l(\theta_i, \psi_j) \cdot x_i$, which incorporated with the leftmost inequality means this strategy must be optimal for the l_{th} attacker.

3. Case Study

In this section, an illustrative case study is conducted to show how the proposed models work. Besides, a practical case study is also used to elaborate and explain how the CPEPs work in real industrial practice. Subsection 3.1 demonstrates the illustrative case study; Subsection 3.2 introduces some basic knowledge of the practical case, while subsection 3.3 illustrates the experimental results by implementing the model and algorithm. Finally, conclusions are summarized in subsection 3.4.

3.1. Illustrative case study

To verify the effectiveness of the proposed model in this paper, we firstly focus on the game between the inspection agency and a certain type of chemical plant in one day. Then, a set of reasonable values for the parameters shown in Table 4 is determined by experts from the inspection agency. The unit for monetary values in Table 4 is RMB (i.e., Yuan(¥)). Here, the probability of successful detection of the violation behaviors through the two inspection resources is set at 0.5 while the probability of successful detection through gas sensors is set at 0.1. Based on historical discharging data, the value of T is set at 2 (see also section 2.1.2). The payoff matrix calculated through the formula (10) and (11) is shown in Table 5. In this table, the chemical plant is the row player while the inspection agency is the column player. Thus payoff in this paper can be represented as (u_a, u_d). Then, the MultiLPs algorithm is used to solve the problem.

Table 4. Reasonable value of parameters.

Parameters	Value	Parameters	Value
C_d	10	P_l^a	-1600
C_a	40	R_l^d	600
R_l^a	800	γ_1	0.1
P_l^d	-400	γ_2	0.5
N	1	T	2
R	1		

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Table 5. Payoff matrix of one-day game between the defender and one attacker.

	θ_1	θ_2	θ_3	θ_4
ψ_1	-800,180	160,-210	160,-210	1120,-600
ψ_2	-440,80	-440,90	520,-310	520,-300
ψ_3	-440,80	520,-310	-440,90	520,-300
ψ_4	-80,-20	-80,-10	-80,-10	-80,0

Based on the payoff matrix in Table 5 and enumerating pure strategies of the attacker, we solve four linear programs correspondingly. Then, the strategy profile is represented as $[q_i;\mathbf{x}]$ and results are illustrated as follows. Comparing the four solutions in corresponding linear programs, it can be concluded that the SSE solution is achieved at $[q_4;\mathbf{x}]=[1;0.2846,0.3404,0.3404,0.0346]$, in which the optimal payoffs are -12.5 and -80 for the inspection agency and the chemical plant respectively. In contrast, if the inspection agency would take the strategy which is denoted as θ_1 in the past, then a payoff at -820 would be brought to her in one day. Two Nash Equilibrium solutions are also acquired in our research, which are at $[q_4;\mathbf{x}]=[1;0.5567,0.1933,0.1933,0.0567]$ and $[q_4;\mathbf{x}]=[1;0.6157,0.1343,0.1343,0.1157]$ if both the inspection agency and the chemical plant choose to play simultaneously. Maximum payoffs for the inspection agency and chemical plant are -15 and -80 respectively in the NE solution. Maximum payoffs for players in one day under different solution concepts are exhibited in Fig.2. The notation of PP in this figure is defined as payoff for the inspection agency, which is acquired from the present practice (i.e., operate the inspection resources all the time). By contrast, it reveals that on the one hand, the SSE solution satisfies the expectation of this paper for the inspection agency receiving more compliance and improving her payoff; on the other hand, the SSE solution is consistent with the assumption proposed in subsection 2.1.4 that the chemical plant will choose the strategy of protecting the environment rather than ruining the environment when his optimal payoff is invariant under different pure strategies. Furthermore, it is obvious that the SSE solution outperforms the other solutions.

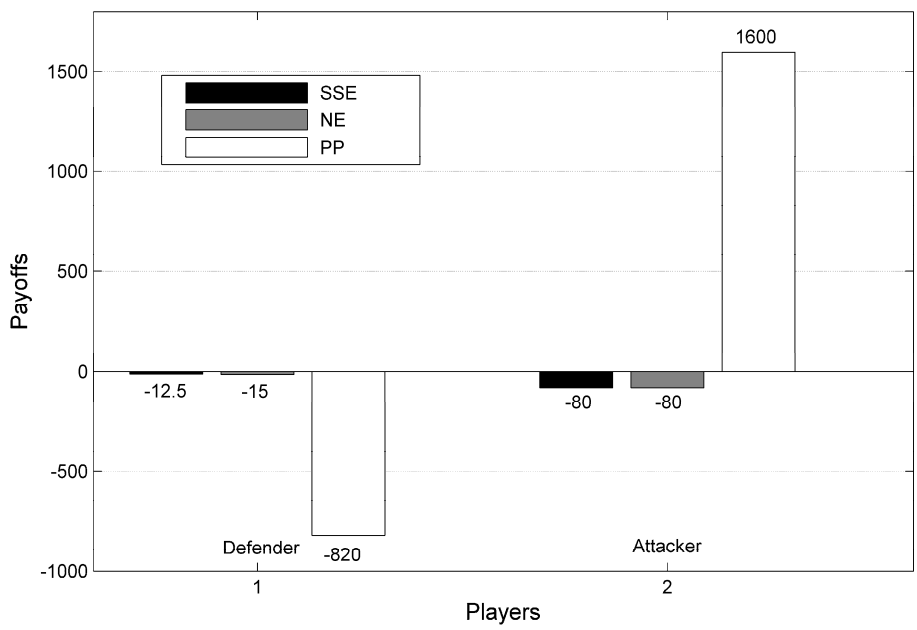

Figure 2. Payoffs for players in a one-day game under different solutions.

From the illustrative case study, we can conclude that it is reasonable to build this problem into SSGs. By combining SSGs with source estimation methods, it not only solves the problem of

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detecting violation behaviors, but also reduces operational costs for the inspection agency. In this way, this paper provides reasonable inspection schedules for the inspection agency to supervise the production process of chemical industries intelligently. Furthermore, atmospheric pollutants' abatement will contribute to improvement of the atmospheric environment.

3.2. Description of the practical case study

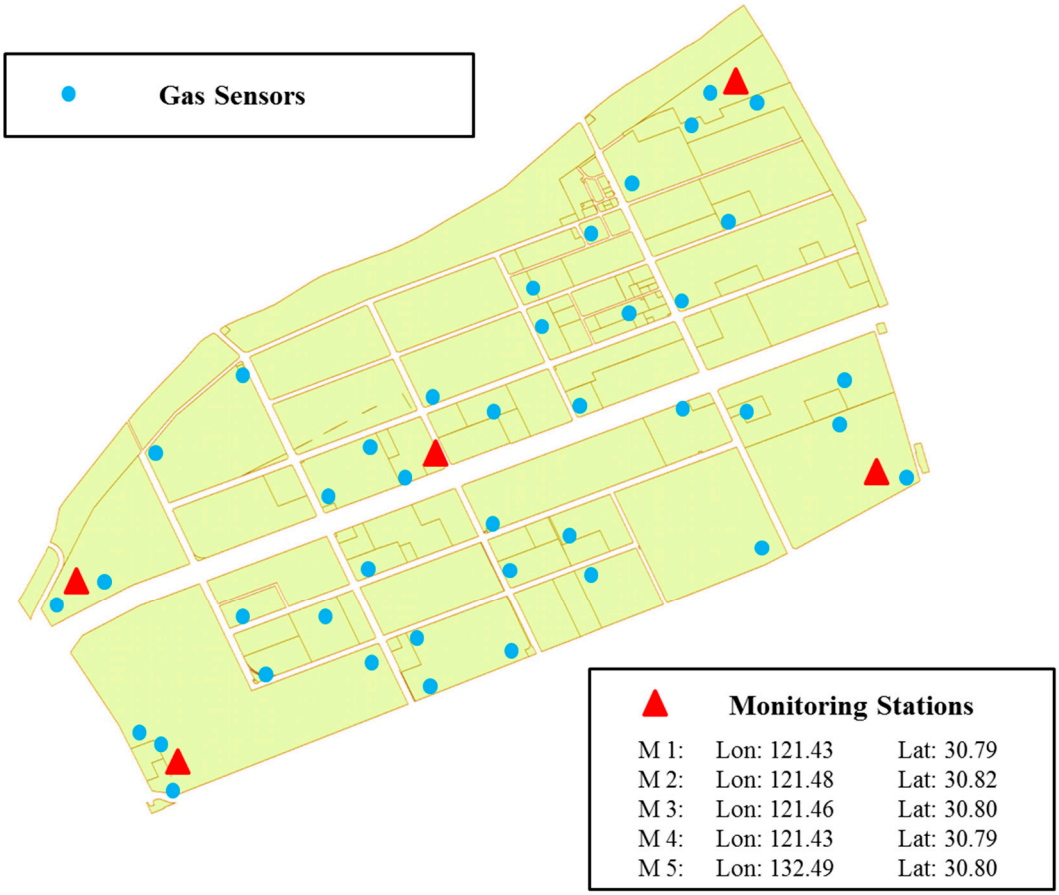

Figure 3. Layout of the case study.

Basically, a chemical industrial park is composed of numerous chemical companies, an inspection agency and functional departments (e.g., hospitals, hotels, police offices and etc.). Moreover, a chemical company may possess several chemical plants in the chemical industrial park. Our practical case is not an exception. Fig.3 shows a refinery from a chemical industrial park in Shanghai, China. The quadrilateral area is main region of the chemical industrial park. All the chemical plants are located in this district and all the inspection resources are also deployed in this area. The triangles indicate high-accuracy air quality monitoring stations while the circles represent gas sensors in Fig.3. Meanwhile, a practicality picture of the two inspection resources is shown in Fig.4. In contrast, the measurement accuracy of high-accuracy air quality monitoring stations is a thousand times more accurate compared to that of gas sensors. These inspection resources (e.g., five monitoring stations and gas sensors) are operating to inspect 55 chemical plants with 243 releasing spots. Indeed, a company in our case usually owns two or three chemical plants. These chemical plants produce similar products, and thus the byproducts generated during the production process are basically the same. Thus, two principles are proposed to classify the chemical plants sharing the same payoffs: (i) byproducts of these chemical plants are almost the same; (ii) these chemical plants belong to the same company and locations of which are adjacent with each other. As a result, only

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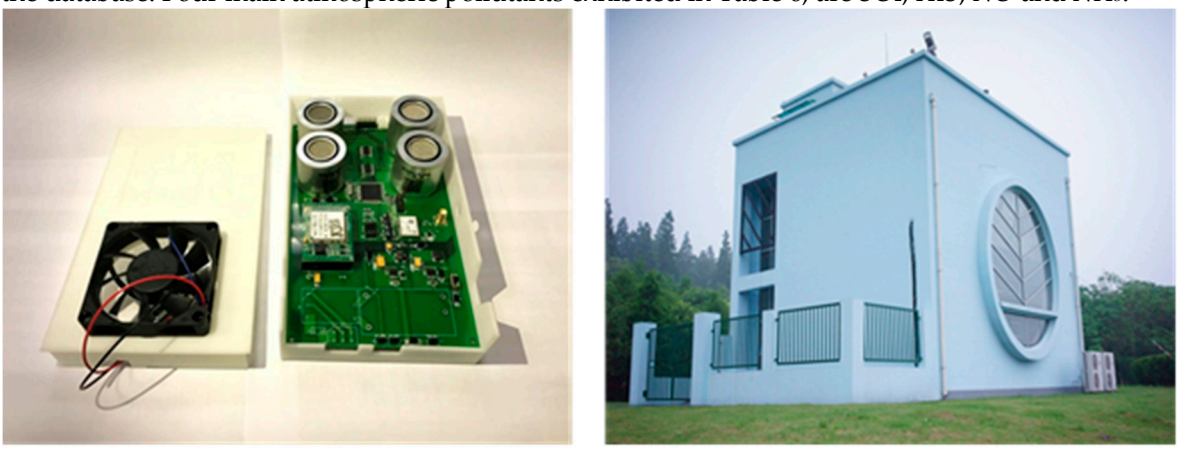
23 chemical plants with byproducts information are considered in our case which is shown in Appendix A. The occurring probabilities of chemical plants classified in one attacker's type are accumulated as the occurring probability of the company. Furthermore, to meet the practical requirements in our modeling process, monitoring stations are open at the same time to collect data or shut down together to reduce costs because monitoring data utilized in source estimation methods are required to be diverse rather than data from only one monitoring station or two monitoring stations. Therefore, five monitoring stations are treated as one resource of inspection agency, not several resources. Sample monitoring data collected by monitoring stations is listed in Table 6. The unit of these atmospheric pollutants is denoted as $\mu g / m^3$. One of the monitoring stations is named as Secco and loading time indicates the time when monitoring data is loaded into the database. Four main atmospheric pollutants exhibited in Table 6, are SO_2, H_2S, NO and NH_3.



(**a**) (**b**)

Figure 4. Inspection resources of inspection agency ((a) is the gas sensors and (b) is one of the high-accuracy air quality monitoring stations).

Table 6. Sample monitoring data collected by monitoring stations [$\mu g / m^3$].

Monitoring Station	Loading Time	SO_2	H_2S	NO	NH_3
Secco	2016-07-26 13:00:00	7.436	2.093	0.938	4.788
Secco	2016-07-26 12:55:00	7.436	2.254	1.072	5.548
Secco	2016-07-26 12:49:00	7.436	2.254	1.072	6.004
Secco	2016-07-26 12:45:00	7.436	2.254	1.072	6.004
Secco	2016-07-26 12:38:00	7.436	2.093	1.072	5.472
Secco	2016-07-26 12:35:00	7.436	2.254	0.938	6.926
Secco	2016-07-26 12:30:00	7.722	2.254	0.938	4.788

Pure strategies for these chemical plants are the same as those in Table 2. Byproducts generated during the production process of the chemical plants are different as the company varies. Therefore, the payoffs for these chemical plants are changing accordingly when byproducts are different. However, it is difficult to determine parameters of each attacker one by one owing to the large number of chemical plants. For the sake of simplicity, the lower bound and upper bound of some parameters (e.g. penalty for the defender and reward for the attacker) are determined by experts from the inspection agency. These parameters are assumed to obey a normal distribution between the intervals of the lower bound and upper bound. It is worth noting that if the models are implemented in industrial practice, all the parameters should be provided by security experts. Here, it is also worth noting that this information concerns estimations from the defender's point of view. A series of parameters are given in Table 7. It can be found that the upper bound and lower bound of the penalty for the inspection agency are set at -350 RMB and -400 RMB respectively when

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she fails to catch the violation behaviors of the chemical plants. Besides, the reward for the inspection agency catching the irregularities of the chemical plants is defined invariant because it accounts for a fixed proportion in the fining. In contrast, the penalty of the chemical plants is set to be invariant because of a fixed fine in the regulation. Furthermore, the upper bound and lower bound of reward for the chemical plants are set at 900 RMB and 800 RMB respectively in the case that he successfully discharges excessive atmospheric pollutants without purification treatment.

Table 7. Value of parameters.

Parameters	Value	Parameters	Value
C_d	10	R_l^a max	900
C_a	40	R_l^a min	800
R_l^d	600	P_l^a	-1600
P_l^d max	-350	N	23
P_l^d min	-400	γ_2	0.5
γ_1	0.1	T	2

3.3. Description of the practical case study

In this subsection, the perfect information of the chemical plants, recognized by the inspection agency, is considered into experiments. Besides, the effect of detection probability on the results is also considered. Therefore, there are two experiments carried out: (i) a CPEP Game is conducted between the inspection agency and 23 chemical plants assuming that perfect information of chemical plants is determined; (ii) the second experiment is conducted to test how the value of γ_2 will impact the decisions of both players. The related parameters used to compute players' payoffs are presented in Appendix B.

Based on the previous monitoring data, the threat of different chemical plants can be calculated. It is assumed that the number of violation behaviors conducted by the l_{th} chemical plant in a year is NUM^l, which will be treated as the threat of the adversary. Thus the prior probabilities of these 23 types of chemical plants can be computed as $p^l = NUM^l / \sum_{l=1} NUM^l$. The corresponding prior probabilities with threats of these chemical plants are shown in Appendix C. With the parameters and models above, the CPEP Game can be solved through the DOBSS.

3.3.1. A one-day game with perfect information of chemical plants

In case that the inspection agency has thorough information about the chemical plants and the chemical plants are able to observe the mixed strategy adopted by the inspection agency. The BSE solution shown in Table 8 is computed through the DOBSS, and the corresponding maximum payoff for the inspection agency is -13.8.

Table 8. Defender's BSE Strategy.

Strategy	Probability
$(open, open)$	0.38
$(open, close)$	0.31
$(close, open)$	0.31
$(close, close)$	0

The probability means that the inspection agency plays strategy $(open, open)$ at probability 0.38, plays strategy $(open, close)$ at probability 0.31, and so forth. In the BSE solution, all the chemical plants are compliant with the inspection agency by choosing the pure strategy of $\{no\ release, no\ release\}$. The detailed defender's payoff with respect to different attacker strategies is

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exhibited in Appendix D. The notations A_P and D_P in Appendix D represent the attacker's payoff and the defender's payoff respectively. Besides, the notation of AP_one means the first pure strategy of the attacker, and so forth for the rest pure strategies. As shown in Appendix D, it is worth noting that if the chemical plants play strategies deviating from the BSE solution, the inspection agency would achieve a worse payoff. However, since the inspection agency knows exact information of the chemical plants, she is able to estimate the chemical plants' best responses to her strategy and play accordingly. Meanwhile, it is also worth noting that chemical plants are believed to play their best response to maximize the inspection agency's payoff in the assumption of SSE. For instance, the payoff of the fifteenth chemical plant is invariant to different pure strategies. But if the fifteenth chemical plant chooses to play ψ_4, the inspection agency would acquire the highest payoff at -13.8 RMB. Currently, the inspection agency keeps the high-accuracy air quality monitoring stations and gas sensors on all the time, which means the defender is playing the strategy of $\{open, open\}$. However, almost none of irregularities conducted by the chemical plants can be detected by the inspection agency without source estimation methods. Therefore, in the present practice, the inspection agency acquired a payoff at -820 RMB and no compliance from the chemical plants. In contrast, it is obvious that the inspection agency improves her payoffs and acquires full compliance from the chemical plants when the CPEP game is played.

3.3.2. γ -testing experiment in one-day game

In common sense, as the value of γ_2 increases (i.e., the prediction probability of violation behavior is more accurate), the corresponding payoff for the inspection agency will be better. In this case, a γ_2 -testing experiment would be conducted to test how the value of γ_2 affect the payoff for the inspection agency and compliance of the chemical plants. In light of that the value of γ_2 must be larger than the value of γ_1 ; the interval of γ_2 studied in this experiment is set between 0.3 and 1. Parameters in Table 7 which are used as inputs to test γ_2 stay invariant except the value of γ_2. Results in detail are shown in the following Table 9 and Fig.5. The notation of Def Strategy denotes the mixed strategy of the defender while the notation of Def Payoff means utility of the management under corresponding mixed strategy. Besides, the notation of Compliance Number indicates the number of chemical plants being compliant with the inspection agency. It can be derived from Table 9 that when the value of γ_2 is smaller than 0.35, the inspection agency would never acquire any compliance from the chemical plants although her mixed strategy converts to the pure strategy of opening the monitoring stations all the time. The critical value of γ_2 for the inspection agency to change her mixed strategy is 0.38. Meanwhile, all the chemical plants are compliant with the inspection agency when the value of γ_2 is higher than 0.38. Moreover, as the value of γ_2 increases, the opening duration of these monitoring stations reduces, and the corresponding payoff for inspection agency improves. The trend is clearly shown in Fig.5. The results indicate that it is essential to improve the predicting ability of source estimation methods.

Table 9. Results of one-day game when the value of γ_2 changes.

Value of γ_2	Def Strategy	Compliance Number	Def Payoff
0.3	[1, 0, 0, 0]	0	-182.7761
0.35	[1, 0, 0, 0]	0	-85.435
0.36	[1, 0, 0, 0]	8	-51.5572
0.37	[1, 0, 0, 0]	19	-25.9322
0.38	[0.9857, 0, 0, 0.0143]	23	-19.7143
0.4	[0.84, 0.08, 0.08, 0]	23	-18.4

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0.5	[0.38, 0.31, 0.31, 0]	23	-13.8
0.6	[0.104,0.448,0.448, 0]	23	-11.04
0.7	[0, 0.46, 0.46, 0.08]	23	-9.2
0.8	[0, 0.3943, 0.3943, 0.2114]	23	-7.8857
0.9	[0, 0.345,0.345, 0.31]	23	-6.9
1.0	[0, 0.3067,0.3067, 0.3866]	23	-6.1333

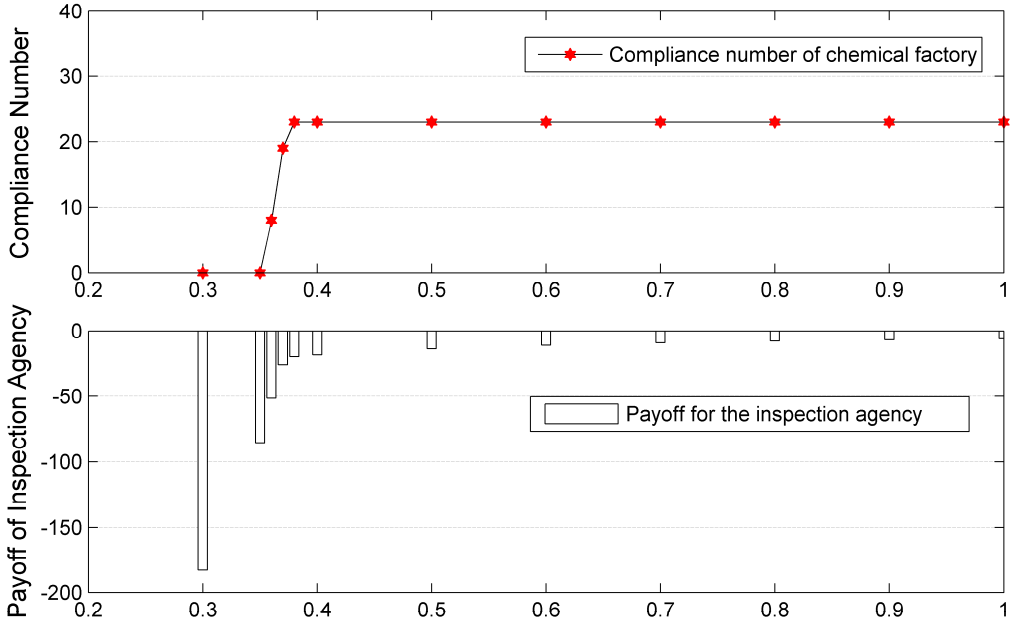

Figure 5. Variable value of γ_2: Number of chemical plants in compliance of environmental regularity.

4. Discussion

In the section of case study, an illustrative case as well as a practical case is implemented to verify the effectiveness of CPEPs. Through the experimental results, two findings are summarized as below.

Our first finding is that the inspection agency is able to achieve compliance effectively from the chemical plants through CPEPs. Learning from the illustrative case and the first experiment in the practical case, all the chemical plants would be compliant in a NE solution, a SSE solution and a BSE solution when CPEPs are played. In these solutions, the inspection agency not only achieves a higher payoff, but also acquires more compliance than in its present practice. Moreover,more compliance from the chemical plants means that the surrounding atmospheric environment will be greatly improved. Another finding is that the predicting ability of source estimation methods determines the performance of CPEPs. Learning from the second experiment in the practical case, it is concluded that as predicting ability of source estimation methods increases, the chemical plants are more likely to be compliant and the corresponding payoff for the inspection agency improves.

Yet, there are some limitations in our results. Adversaries are assumed to be fully rational in BSE solutions while adversaries ought to be modeled according to bounded rationality in SSGs where attacks occur frequently. Due to a limited time for planning the attacks, attackers are often not the perfectly rational payoff maximizers. Thus, it is necessary incorporating a behavior model of adversaries or robust optimization techniques with source estimation methods to deal with this difficult problem. Besides, the parameters related to the chemical plants are given by domain

experts from the inspection agency, the exact value of which may be inaccurate. In case that the inspection agency does not know the exact parameters of the chemical plants, she may assume that these parameters are located between certain minimal and maximal values. In that case, a repeated game with the defender's uncertainty on the attacker's parameters should be played.

5. Conclusions

This paper applies SSGs into a new domain of environmental protection, and incorporates source estimation methods. The work of our research is to aid inspection agencies in effectively scheduling inspections of chemical production processes through providing mixed strategies incorporating various real-world uncertainties and constraints. Previous work in this domain falls short of generating executable solutions for inspection agencies due to the following challenges: (i) inspection resources are limited and not fully utilized; (ii) source estimation methods are not applied in chemical industry management; (iii) the number of adversaries is huge in this field. In addressing these challenges, this paper has advanced science with three novelties. The first novelty is incorporating SSGs with source estimation methods intelligently. Second, two inspection resources (monitoring stations and gas sensors) are modeled into CPEPs. Third, simple data analysis on discharging information of adversaries is utilized to construct CPEPs. Our experimental results show that the inspection agency is able to achieve more compliance from the chemical plants and improve her payoff by playing CPEPs.

Future research can take a number of directions. First, we can apply our models and algorithms into real industrial practice. Furthermore, violation information will be collected to learn about the behavior of adversaries. Robust optimization techniques combined with the behavior model of adversaries will improve the performance of our models and algorithms in providing monitoring stations' inspection schedules. Another interesting future research direction is limited observation of attackers on the defender's mixed strategy. In repeated SSGs, the attacks are usually frequent and thus complete observation on the defender's mixed strategy is hard to implement. Observation errors modeled in this research will be more practical. Apart from the above directions, a repeated game incorporating the defender's uncertainty on the attacker's parameters is an interesting path of future research.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A Information of these twenty-three chemical plants

Table A. Main byproducts information of 23 chemical plants.

Chemical plant	Pollutants Generated
chemical plant a	*Particulates*
chemical plant b	CO, SO_2, NO_x, HF, HCL,
chemical plant c	SO_2, NO_x
chemical plant d	HCL, CH_3CL, CH_3COCH_3, CH_2CL_2, C_6H_6, C_7H_8
chemical plant e	SO_2, NO_x, CO, VOC
chemical plant f	NO_x, C_7H_8, CO, SO_2, HCL, CL_2
chemical plant g	HCL, C_7H_8, C_8H_{10}, C_6H_5CL, C_2H_5CL, SO_2, NO_x, VOC, HCL
chemical plant h	SO_2, *Particulates*
chemical plant i	SO_2, NO_x, CO

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chemical plant j	*CO, SO_2, NO_x, CH_3OH, CH_2O*
chemical plant k	*SO_2, NO_x, Particulates*
chemical plant l	*NO_x*
chemical plant m	*CO, SO_2, NO_x, HCL, CL_2, Particulates*
chemical plant n	*CH_3COCH_3*
chemical plant o	*SO_2, NO_x, VOC*
chemical plant p	*NO_x, VOC, NH_3*
chemical plant q	*SO_2, NOx, CO, HF, HCL, C_6H_6*
chemical plant r	*NO_x, VOC*
chemical plant s	*C_6H_7N, SO_2, NO_x, HF, HCL*
chemical plant t	*$COCL_2$, HCL, CO*
chemical plant u	*$COCL_2$, HCL, CO SO_2, NO_x,*
chemical plant v	*C_6H_5CL, $CHCL_3$, C_2H_5CL, CCl_4*
chemical plant w	*NH_3, CO SO_2, NO_x,*

Appendix B Related parameters used for solving CPEPs

Table B. Related parameters used in practical case study for solving CPEPs.

Chemical plant	Penalty for Defender	Reward for Attacker
chemical plant a	-368	854
chemical plant b	-361	887
chemical plant c	-353	826
chemical plant d	-351	832
chemical plant e	-391	812
chemical plant f	-393	894
chemical plant g	-365	865
chemical plant h	-396	848
chemical plant i	-374	864
chemical plant j	-373	855
chemical plant k	-357	865
chemical plant l	-376	854
chemical plant m	-380	872
chemical plant n	-366	852
chemical plant o	-363	900
chemical plant p	-374	822
chemical plant q	-383	810
chemical plant r	-393	811
chemical plant s	-371	806
chemical plant t	-387	840
chemical plant u	-398	845
chemical plant v	-362	836
chemical plant w	-388	877

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Appendix C Prior probabilities of chemical plants

Table C. Prior probabilities of different chemical plants.

Chemical plant	Prior Probability	Violation Number
chemical plant a	0.0503	106
chemical plant b	0.0645	136
chemical plant c	0.0323	68
chemical plant d	0.0517	109
chemical plant e	0.0342	72
chemical plant f	0.0517	109
chemical plant g	0.0527	111
chemical plant h	0.0243	51
chemical plant i	0.0327	69
chemical plant j	0.0313	66
chemical plant k	0.0517	109
chemical plant l	0.0598	126
chemical plant m	0.0371	78
chemical plant n	0.0565	119
chemical plant o	0.0517	109
chemical plant p	0.0214	45
chemical plant q	0.0484	102
chemical plant r	0.0389	82
chemical plant s	0.0626	132
chemical plant t	0.0214	45
chemical plant u	0.0422	89
chemical plant v	0.0404	85
chemical plant w	0.0422	89

Appendix D Defender's Payoff under different attacker strategies

Table D. Defender's payoff w.r.t different attacker strategies.

	AP_One		AP_Two		AP_Three		AP_Four	
Chemical plant	A_P	D_P	A_P	D_P	A_P	D_P	A_P	D_P
chemical plant a	-137.4	-21.86	-108.7	-17.83	-108.7	-17.83	-80	-13.8
chemical plant b	-96.22	-13.13	-88.11	-13.46	-88.11	-13.46	-80	-13.8
chemical plant c	-172.4	-3.144	-126.2	-8.472	-126.2	-8.472	-80	-13.8
chemical plant d	-164.9	-0.648	-122.4	-7.224	-122.4	-7.224	-80	-13.8
chemical plant e	-189.8	-50.57	-134.9	-32.18	-134.9	-32.18	-80	-13.8
chemical plant f	-87.49	-53.06	-83.74	-33.43	-83.74	-33.43	-80	-13.8
chemical plant g	-123.7	-18.12	-101.8	-15.96	-101.8	-15.96	-80	-13.8
chemical plant h	-144.9	-56.81	-112.4	-35.30	-112.4	-35.30	-80	-13.8
chemical plant i	-124.9	-29.35	-102.5	-21.58	-102.5	-21.58	-80	-13.8
chemical plant j	-136.2	-28.10	-108.1	-20.95	-108.1	-20.95	-80	-13.8
chemical plant k	-123.7	-8.136	-101.8	-10.97	-101.8	-10.97	-80	-13.8

chemical plant l	-137.4	-31.85	-108.7	-22.82	-108.7	-22.82	-80	-13.8
chemical plant m	-114.9	-36.84	-97.47	-25.32	-97.47	-25.32	-80	-13.8
chemical plant n	-139.9	-19.37	-109.95	-16.58	-109.95	-16.58	-80	-13.8
chemical plant o	-80	-15.62	-80	-14.71	-80	-14.71	-80	-13.8
chemical plant p	-177.3	-29.35	-128.7	-21.58	-128.7	-21.58	-80	-13.8
chemical plant q	-192.3	-40.58	-136.2	-27.19	-136.2	-27.19	-80	-13.8
chemical plant r	-191.1	-53.06	-135.5	-33.43	-135.5	-33.43	-80	-13.8
chemical plant s	-197.3	-25.61	-138.7	-19.70	-138.7	-19.70	-80	-13.8
chemical plant t	-154.9	-45.58	-117.4	-29.69	-117.4	-29.69	-80	-13.8
chemical plant u	-148.6	-59.30	-114.3	-36.55	-114.3	-36.55	-80	-13.8
chemical plant v	-159.9	-14.38	-119.9	-14.09	-119.9	-14.09	-80	-13.8
chemical plant w	-108.7	-46.82	-94.35	-30.31	-94.35	-30.31	-80	-13.8

References

1. Hsu Angel, E.D., Levy MA, Sherbinin Alex. *2016 environmental performance index*. New Haven, CT: Yale University.
2. Fu, X.; Feng, T.; Jiang, C. Research progress on atmospheric pollution and human health in china. **2015**.
3. Congress, S.C.O.P.S. Law of the people's republic of china on the prevention and control of atmospheric pollution. *Environmental Policy Collection* **2000**.
4. Dalton, S.; Tierney, M. Collections: Earth and environmental science collection development policy. *Nyu Libraries* **2007**.
5. Tambe Milind. *Security and game theory: Algorithms, deployed systems, lessons learned*. Cambridge University Press: 2012.
6. Zhen Wang; Yong Yuan; Bo An; Mingchu Li; Feiyue Wang. An overview of security games. *Journal of Command and Control* **2015**, *1*, 121-149.
7. Korzhyk D; Conitzer V; Parr R. Solving stackelberg games with uncertain observability. In *International Conference on Autonomous Agents and Multi-agent Systems. International Foundation for Autonomous Agents and Multi-agent Systems*, 2011; pp 1013-1020.
8. Kar, D.; Fang, F.; Delle Fave, F.; Sintov, N.; Tambe, M. In *A game of thrones: When human behavior models compete in repeated stackelberg security games*, International Conference on Autonomous Agents and Multiagent Systems, 2015; pp 1381-1390.
9. Nguyen, T.H.; Sinha, A.; Gholami, S.; Plumptre, A.; Joppa, L.; Tambe, M.; Driciru, M.; Wanyama, F.; Rwetsiba, A.; Critchlow, R., *et al.* Capture: A new predictive anti-poaching tool for wildlife protection. In *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems*, International Foundation for Autonomous Agents and Multiagent Systems: Singapore, Singapore, 2016; pp 767-775.
10. Pavlova, Y.; Reniers, G. A sequential-move game for enhancing safety and security cooperation within chemical clusters. *Journal of Hazardous Materials* **2011**, *186*, 401-406, DOI:http://dx.doi.org/10.1016/j.jhazmat.2010.11.013.
11. Reniers, G. An external domino effects investment approach to improve cross-plant safety within chemical clusters. *Journal of Hazardous Materials* **2010**, *177*, 167-174, DOI:http://dx.doi.org/10.1016/j.jhazmat.2009.12.013.

12. Reniers, G.; Cuypers, S.; Pavlova, Y. A game-theory based multi-plant collaboration model (mcm) for cross-plant prevention in a chemical cluster. *Journal of Hazardous Materials* **2012**, *209*, 164-176, DOI:http://dx.doi.org/10.1016/j.jhazmat.2012.01.004.
13. Reniers, G.; Dullaert, W.; Karel, S. Domino effects within a chemical cluster: A game-theoretical modeling approach by using nash-equilibrium. *Journal of Hazardous Materials* **2009**, *167*, 289-293, DOI:http://dx.doi.org/10.1016/j.jhazmat.2008.12.113.
14. Reniers, G.; Dullaert, W.; Visser, L. Empirically based development of a framework for advancing and stimulating collaboration in the chemical industry (asc): Creating sustainable chemical industrial parks. *Journal of Cleaner Production* **2010**, *18*, 1587-1597, DOI:http://dx.doi.org/10.1016/j.jclepro.2010.07.013.
15. Reniers, G.; Soudan, K. A game-theoretical approach for reciprocal security-related prevention investment decisions. *Reliability Engineering & System Safety* **2010**, *95*, 1-9, DOI:http://dx.doi.org/10.1016/j.ress.2009.07.001.
16. Zhang, L.; Reniers, G. A game-theoretical model to improve process plant protection from terrorist attacks. *Risk Anal* **2016**, *36*, 2285-2297, DOI:10.1111/risa.12569.
17. Zhang, L.; Reniers, G.; Qiu, X. Playing chemical plant protection game with distribution-free uncertainties. *Reliability Engineering [?] System Safety* **2017**.
18. Fang, F.; Nguyen, T.H. Green security games: Apply game theory to addressing green security challenges. *SIGecom Exch.* **2016**, *15*, 78-83, DOI:10.1145/2994501.2994507.
19. Johnson, M.P.; Fang, F.; Tambe, M. Patrol strategies to maximize pristine forest area. In *Proceedings of the Twenty-Sixth AAAI Conference on Artificial Intelligence*, AAAI Press: Toronto, Ontario, Canada, 2012; pp 295-301.
20. Fei Fang; Nguyen Thanh H. Deploying paws: Field optimization of the protection assistant for wild life security. In *Twenty-eighth IAAI Conference on Innovative Applications of Artificial Intelligence*, IAAI Press: 2016.
21. Haskell, W.B.; Kar, D.; Fang, F.; Tamb, M.; Cheung, S.; Denicola, L.E. Robust protection of fisheries with compass. In *Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence*, AAAI Press: Québec City, Québec, Canada, 2014; pp 2978-2983.
22. Fang, F.; Stone, P.; Tambe, M. When security games go green: Designing defender strategies to prevent poaching and illegal fishing. In *Proceedings of the 24th International Conference on Artificial Intelligence*, AAAI Press: Buenos Aires, Argentina, 2015; pp 2589-2595.
23. Beijing safety equipment manufacturing Co. Ltd. *Operating instruction of gasmonitor*.
24. Munoz-Garcia, F.; Toro-Gonzalez, D. Simultaneous-move games with incomplete information. In *Strategy and game theory: Practice exercises with answers*, Munoz-Garcia, F.; Toro-Gonzalez, D., Eds. Springer International Publishing: Cham, 2016; pp 217-236.
25. Munoz-Garcia, F.; Toro-Gonzalez, D. Pure strategy nash equilibrium and simultaneous-move games with complete information. In *Strategy and game theory: Practice exercises with answers*, Munoz-Garcia, F.; Toro-Gonzalez, D., Eds. Springer International Publishing: Cham, 2016; pp 25-60.
26. Brown, G.; Carlyle, M.; et al. Defending critical infrastructure. *Interfaces* **2006**, *36*, 530-544, DOI:10.1287/inte.1060.0252.
27. Letchford, J.; Korzhyk, D.; Conitzer, V. On the value of commitment. *Autonomous Agents and Multi-Agent Systems* **2014**, *28*, 986-1016, DOI:10.1007/s10458-013-9246-9.
28. Gibbons, R.; Gibbons, R. *Game theory for applied economists*. Princeton University Press: 1992.

29. Korzhyk, D.; Yin, Z.; Kiekintveld, C.; Conitzer, V.; Tambe, M. Stackelberg vs. Nash in security games: An extended investigation of interchangeability, equivalence, and uniqueness. *J. Artif. Int. Res.* **2011**, *41*, 297-327.
30. Leitmann, G. On generalized stackelberg strategies. *Journal of Optimization Theory and Applications* **1978**, *26*, 637-643, DOI:10.1007/BF00933155.
31. Von Stengel, B.; Zamir, S. Leadership games with convex strategy sets. *Games and Economic Behavior* **2010**, *69*, 446-457, DOI:http://dx.doi.org/10.1016/j.geb.2009.11.008.
32. Conitzer, V.; Sandholm, T. Computing the optimal strategy to commit to. In *Proceedings of the 7th ACM conference on Electronic commerce*, ACM: Ann Arbor, Michigan, USA, 2006; pp 82-90.
33. Harsanyi, J.C.; Selten, R. A generalized nash solution for two-person bargaining games with incomplete information. *Management Science* **1972**, *18*, 80-106, DOI:10.1287/mnsc.18.5.80.
34. Paruchuri, P.; Pearce, J.P.; Marecki, J.; Tambe, M.; Ordonez, F.; Kraus, S. Playing games for security: An efficient exact algorithm for solving bayesian stackelberg games. In *Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems - Volume 2*, International Foundation for Autonomous Agents and Multiagent Systems: Estoril, Portugal, 2008; pp 895-902.