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A REAL-TIME ROLLING APPROACH TO PERCEIVING THE TIME POINT OF POSSIBLY ABNORMAL CONSUMPTION OF OIL

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Abstract. *Stockouts are serious accidents at gas stations in China. However, it is hard to capture the abnormal consumption timely to avoid the occurrence of a stockout due to the stochastic arrivals of demands. In this paper, a real-time rolling approach to perceiving the time point of possibly abnormal consumption is developed by excluding the strictly secure periods. The proposed approach integrates dynamic contexts, current states and future contexts to support the real-time perceiving of possibly abnormal time points. A simulation system is implemented on the Arena simulation platform, through which we deeply analyze the simulation results to prove the effectiveness of the proposed real-time rolling approach.*
Keywords: Rolling approach, Abnormal consumption, Context, Simulation

1. **Introduction.** At gas stations, it is hard to capture the abnormal consumption timely due to the stochastic arrivals of demands. If we cannot take reasonable precautions in real time to respond to the abnormal consumption, a stockout will occur. However, as an important material of production and subsistence, the oil must be supplied promptly. Otherwise, it will disrupt the social order seriously and even result in chaos. Thus, it is important to perceive the time point of possibly abnormal oil consumption in real time to issue warnings timely and finally guarantee the supplement.

The anomaly of oil consumption at a gas station is affected by the current context, such as the consumption rate of oil, the remaining arrival time of tankers, and the current oil stock levels. Thus, the possibly abnormal time point, which we use t_a to denote hereinafter, changes constantly and it is hard to be captured in real time. This special type of anomaly for possibly abnormal consumption of oil has the characteristics of both online contextual anomalies and temporal dynamics, which means that the time point of anomaly depends on both the current context and the temporal dynamics in a system. We can call this special type of anomaly as dynamic online contextual anomaly. This type of anomaly is common in many applications such as monitoring oil overflowing, monitoring the mine environment and other security monitoring, where great economic losses even the loss of life would occur if real anomalies happen. Traditionally, domain experts are responsible for reporting the abnormal consumption of oil with their experience and expertise. Such a manual process is time-consuming and error-prone. As the consumption of oil is likely to change over time, such temporal dynamics is difficult to be captured by the domain experts because they may not be able to refresh their knowledge quickly enough.

In order to perceive the time point t_a timely, this paper proposes a real-time rolling approach. It excludes the strictly secure periods by considering the real-time context

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captured by the technology of Internet of Things (IoT) and by updating the detected time window. The real-time rolling approach can perceive the possibly anomaly consumption time in order to judge whether the stockout will occur. As now we can utilize the IoT technologies equipped with the oil distribution system to capture the real-time contextual information, such as the current consumption rate of oil, the current stock of the gas station and the time when the tanker arrives at the gas station, we get the opportunity to develop a process to issue the early warning of the abnormal consumption automatically. In the process, the perceived possibly abnormal time t_a is the starting point of the trend analysis of the oil consumption. It means that by excluding the strictly secure periods, at the possibly abnormal time t_a, trend analysis of the oil consumption can be triggered to determine whether it will evolve to be a real anomaly. If it is, an early warning will be issued to alert decision makers to take measures at the right time. Based on the real-time rolling approach, we can improve the efficiency of the online trend analysis of oil consumption by just making trend analysis at possibly abnormal time t_a. Moreover, this approach does not only facilitate the process of online trend analysis that does not need to work all time but just be triggered at t_a, but also can correctly identify all the possibly dynamic contextual anomalies by processing the dynamic context and online data.

The remaining parts of the paper are organized as follows. Section 2 reviews the related work. Section 3 proposes the approach. Section 4 implements the approach in the Arena simulation platform and analyzes the simulation results deeply to prove the effectiveness of the approach. Finally, in Section 5, conclusions are drawn and further study is introduced.

2. **Related Work.** As we have described, whether the consumption of oil at a time point is anomalous is related with a specific context. In other words, it depends on the context consisting of the current consumption rate of oil, the remaining arrival time of the tanker, the current inventory level of the gas station at this time point. A higher consumption rate of oil may be anomalous when the inventory level of the gas station is low or the remaining arrival time of the tanker is long, while it may be non-anomalous when the inventory level is high or the remaining arrival time is short. Besides, the perception of the possibly abnormal time point, t_a, at a gas station is based on the data stream from the liquid-level gauge and the other real-time contextual information captured by the IoT technologies. Several application domains collect sequence data in a streaming type. Such domain often requires the anomalies to be detected in such sequences online, i.e., as soon as they occur. Hence, it is related to the online contextual anomaly detection.

According to the method of handling the real-time data stream, existing researches with regard to online contextual anomaly detection focus on the following aspects: (1) establish the conditional anomaly detection (CAD) model in the offline phase; (2) construct the normal pattern according to history data in the offline phase; (3) utilize the structure in data stream.

(1) Establish the Conditional Anomaly Detection (CAD) Model

An intuitive way in this field is to establish the conditional anomaly detection (CAD) model in the offline phase, then using the CAD to detect anomaly when the data arrives.

The conditional anomaly detection (CAD) is first introduced in [1]. The authors assume that the attributes are already partitioned into contextual and behavioral attributes. The contextual data and the behavioral data are partitioned using mixture of Gaussian models. Then, the mapping between the context and the behavior is learned to get the anomaly score. Based on the conditional anomaly detection framework in [1], the work in [2,3] focuses on instance-based methods of detecting conditional anomalies. In [4], the framework is extended to identify multivariate conditional anomalies where they are interested in the patterns exhibit dependencies among individual clinical actions conditioned on the patient condition. In [5], the authors introduce the online conditional anomaly detection in multivariable for transformer monitoring. In the online phase, the most recent measurements are input to the CAD models to get anomaly score.

(2) Construct Normal Pattern

An intuitive way in this field is to construct normal patterns in the offline phase and to detect anomaly by comparing the recent data with the normal pattern in real time. The method is usually used to anomalous trajectory detection by using the rich GPS historical data.

In [6-8], the online anomalous trajectory detection is split into an offline preprocessing phase and an online detection phase. The offline phase is in charge of collecting and classifying a set of historical trajectories. In the online phase, the authors process a series of incoming GPS points and detect anomalous routes by comparing the latter against time-dependent historically "normal" routes.

(3) Utilize the Structure in Data Stream

An intuitive way in this field is to calculate the stream anomaly score from the recent historical instances stored in a sliding window by taking the historical information of a data stream into consideration.

A generic technique in this category can be described as follows. In [9], the Markov model is constructed and processed by a proposed recursive Bayesian filter to infer an optimal probability distribution of the potential anomalous driving behaviors dynamically over time. In [10], the historical information of the stream is incorporated to quantify the stream anomaly. The paper uses the stream anomaly score to quantify how significant a stream behaves differently from the majority of the stream.

In general, the research on the online contextual anomaly detection is to identify the anomaly of data stream based on its normal behaviors in the specific context. Once the current behavior of a stream is different from its normal behaviors (identified based on historical data), it is considered abnormal. However, the context influencing the abnormal consumption of oil changes over time, and it is hard to construct a specific context model to define the anomaly. We call this special type of anomaly as dynamic online contextual anomaly as described earlier. Thus, we develop a real-time rolling approach to capturing all the possibly dynamic contextual anomalies by processing the dynamic context and online data.

3. The Real-Time Rolling Approach.

Taking the situations of the oil logistics system in both theory and practice into consideration, there are following basic premises.

(1) The tank truck with oil is travelling to the gas station at a constant speed.

(2) All road conditions are stable without any disruption.

(3) The refueling rate of each fuel dispenser at the gas station is the same.

(4) The oil logistics system is equipped with IoT technologies, such as tank trucks equipped with GPS that can get their real-time positions, and gas stations equipped with liquid-level gauges that can get their real-time stock levels.

The following parameters will be used in the description of the approach.

n, the total number of fuel dispensers at the gas station;

i, the number of fuel dispensers at work, and $i \leq n$;

v_{each}, the refueling rate of each fuel dispenser, $v_{each} > 0$;

v_0, the perceived original consumption rate of oil, $v_0 \geq 0$;

S_0, the original oil stock of the gas station, $S_0 \geq 0$;

t_0, the perceived original time, $t_0 \geq 0$;

v_{t_c}, the perceived current consumption rate of oil, $v_{t_c} \geq 0$;

S_c, the current oil stock of the gas station, $S_c \geq 0$;

t_c, the perceived current time, $t_c \geq 0$;
S_s, the safe stock, $S_s > 0$;
d_c, the perceived distance between the current location of the tanker traveling to the gas station and the gas station, $d_c \geq 0$;
v_{tanker}, the speed of tanker, $v_{tanker} > 0$;
T, the travel time between the current location of the tanker and the gas station, and $T > 0$.

As the real-time rolling approach is developed based on the analysis of the data stream from the liquid-level gauge of the gas station, we describe the data characteristics in Section 3.1 before illustrating the approach in Section 3.2.

3.1. **Data analysis.** By observing the data stream from the liquid-level gauge and investigating the individual or joint working state of the fuel dispensers, it can be concluded that the changes in the data are determined by the number of fuel dispensers which are working at the same time. Thus, the consumption rate of oil can only be $i * v_{each}$ ($i = 0, 1, 2, \ldots, n$). Taking a gas station with 4 fuel dispensers of a kind totally as an example, a part of the data depicted by the consumption rates of oil is shown in Figure 1, where the biggest consumption rate is $4 * v_{each}$, and the other rates are 0, v_{each}, $2 * v_{each}$, and $3 * v_{each}$.

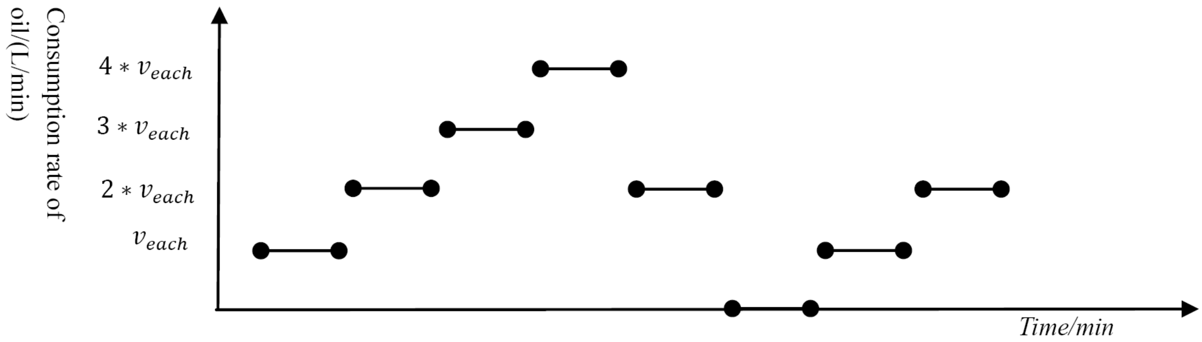

Figure 1. A part of the data depicted by the consumption rates of oil

3.2. **The flowchart of the real-time rolling approach.** Considering the current consumption rate of oil and other context, we determine the possibly abnormal point t_a by excluding the strictly secure periods.

The flowchart of the real-time rolling approach is shown in Figure 2. The specific algorithm steps are as follows.

Step (1): Firstly, evaluate the current remaining safe oil stock of the gas station $\Delta s = S_c - S_s$. If all the fuel dispensers work together, the oil will be consumed at the maximum consumption rate $v_{\max} = n * v_{each}$. We judge whether the allowed duration time of consumption $t_{\min} = \frac{\Delta s}{v_{\max}}$ exceeds the time $= \frac{d_c}{v_{tanker}}$. If it exceeds, it means that there will be no stockout events before the tanker arrives at the gas station and there are no possibly abnormal points. Otherwise, proceed to step (2).

Step (2): Secondly, by using the current initial consumption rate of oil v_0, we can get the allowed duration time of consumption $t_k = t_0 + (S_c - S_s)/v_0$. Then, we need to determine whether t_k exceeds the time T. If it exceeds, then update the value of t_k to T. Otherwise, proceed to step (3).

Step (3): In the range of t_k, it is required to perceive whether the real-time oil consumption rate v_{t_c} exceeds the initial speed v_0. If it exceeds, then update $t_0 = t_c$, $v_0 = v_{t_c}$,

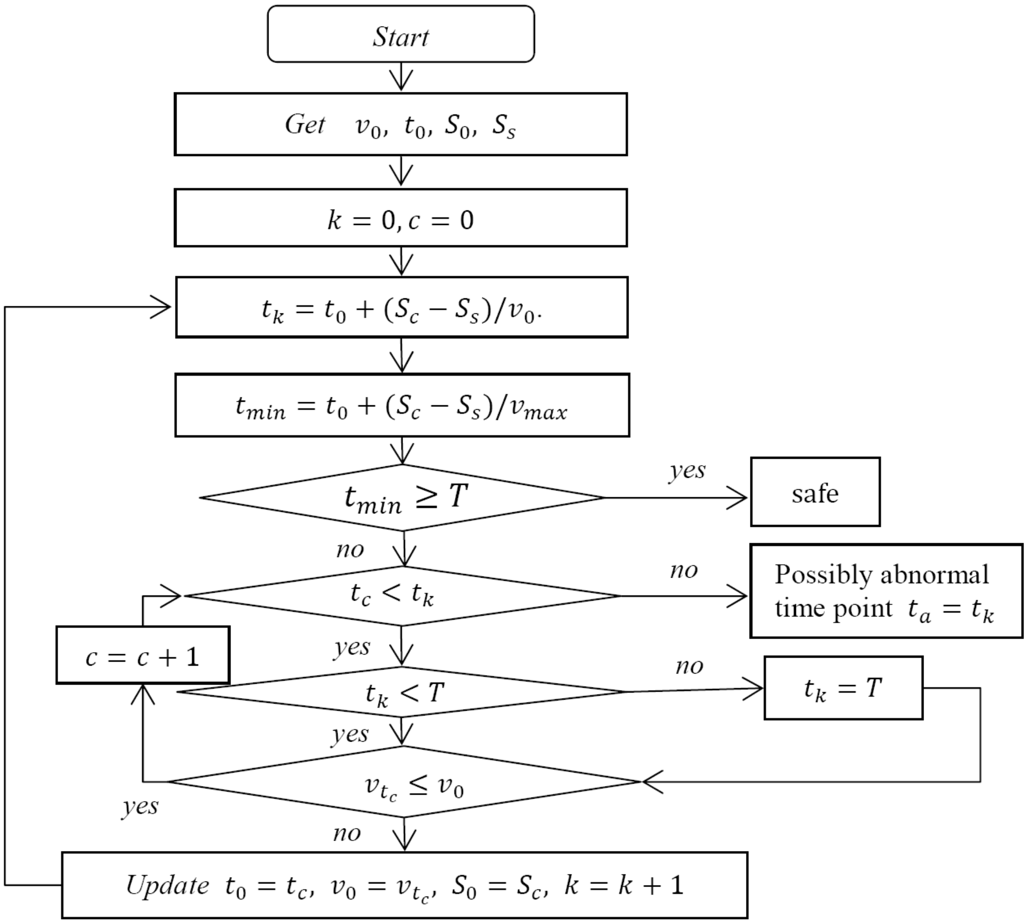

FIGURE 2. The flowchart of the real-time rolling approach

$S_0 = S_c$ by the real-time values of them and let $k = k + 1$ and go back to step (1). Otherwise, continually judge if the current time t is within the range of t_k.

4. The Implementation of the Rolling Approach on the Arena Simulation Platform.

4.1. **Design of experiment.** As there are no benchmark problems for oil consumption in the oil distribution system, this paper simulates the oil consumption of the gas station and the running conditions of the tanker in the oil distribution system in the Arena to verify the effectiveness of the approach.

Based on the investigation of the running conditions of gas stations and tankers in Dalian, we know the running situation of a gas station as follows. At a gas station, the number of fuel dispensers is even and each fuel dispenser keeps the same refueling rate v_{each} when working. When a car gets to a gas station, it has to wait for a time (when a worker pulls out a refueling gun and plugs it into the car's tanker) and then the car starts refueling causing the oil consumption. After refueling, a time of pulling out the gun and payment is needed and finally the car leaves. Besides, the tanker visits the gas stations according to the distribution plan. In all, the factors that influence the oil consumption are the distribution rules of tankers' and cars' arrival intervals and the service times.

In this paper, we simulate a basic example enabling users to expand according to the actual situation. We assume that there are $n = 4$ fuel dispensers at the gas station, the refueling rate of each fuel dispenser is $v_{each} = 10$ and the oil will be consumed at the maximum consumption rate $v_{\max} = n * v_{each} = 40$. Besides, we can get the current consumption rate of oil v_{t_c}, the current oil stock of the gas station S_c, the current time t_c and the travel time between the current location of the tanker and the gas station T timely.

The modelling and simulations of Figure 2 are implemented by using the "Basic Process", "Advanced Transfer" and "Flow Process" templates in Arena. In Arena, we set the length of simulation as 2days ∗ 24hours/day. We change the key parameters of the distribution of the arrival time intervals of cars, the distribution of oiling time and the distribution of the arrival time intervals of tankers to verify the effectiveness of the approach. Besides, we set the safety stock as 120 to decide whether to make early warnings simply.

Parts of the simulation system are shown in Figure 3, Figure 4 and Figure 5. In Figure 3, we simulate the workflow for cars refueling at the gas station. In Figure 4, we simulate the oil tanker to get T. In Figure 5, we simulate the time event to make a signal at t_k.

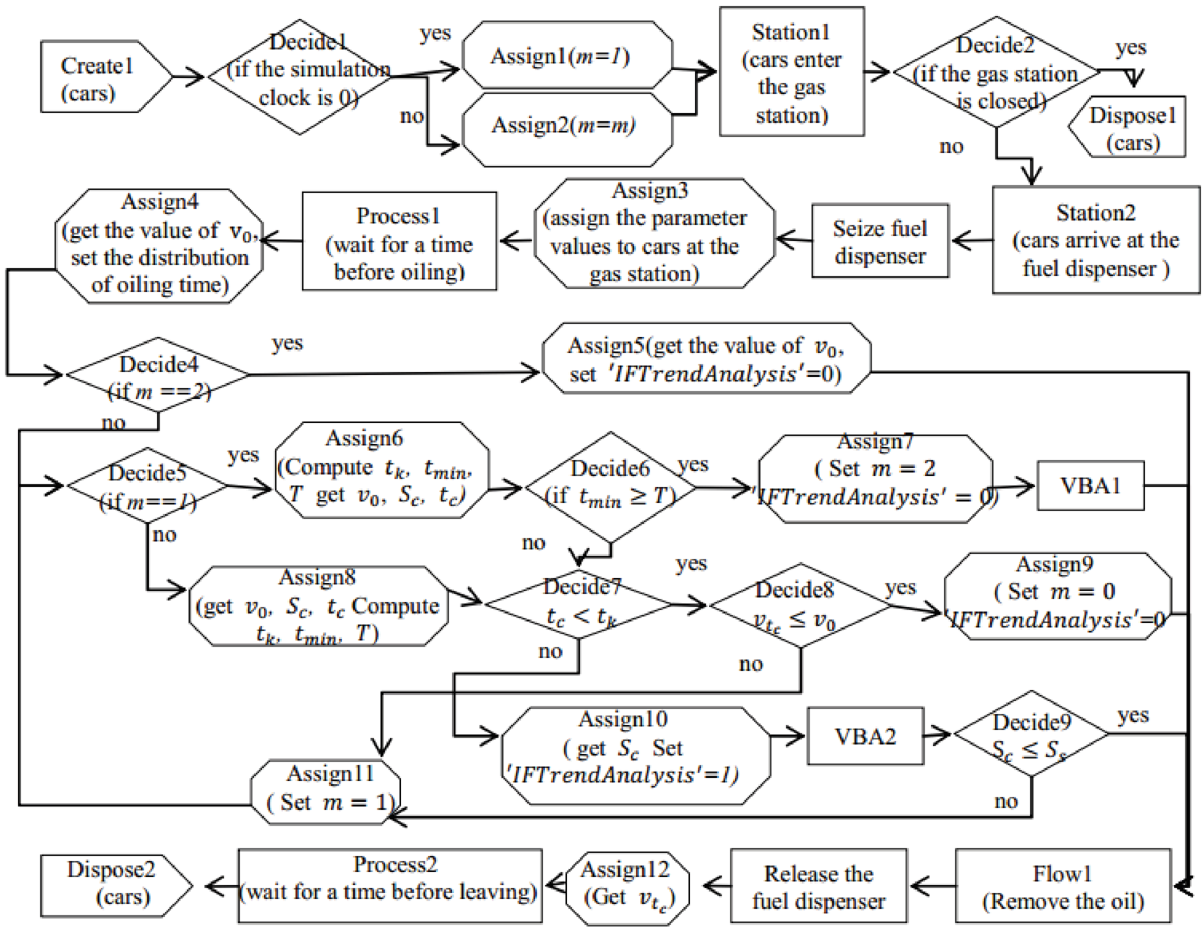

FIGURE 3. The simulation of cars at the gas station

Some of the modules are as follows.

1) Create Module, it simulates the arrival of entities, such as, cars and oil tankers.

2) Station Module, it can provide the place of activities for tankers and cars.

3) Route Module, it can provide the route and the consuming of time for tankers and cars.

4) Decide Module, it can detect the oil consumption state.

5) Assign Module, it can assign the value under each simulation to the defined variable, or assign the defined initial value and static variable value to the model. In this paper,

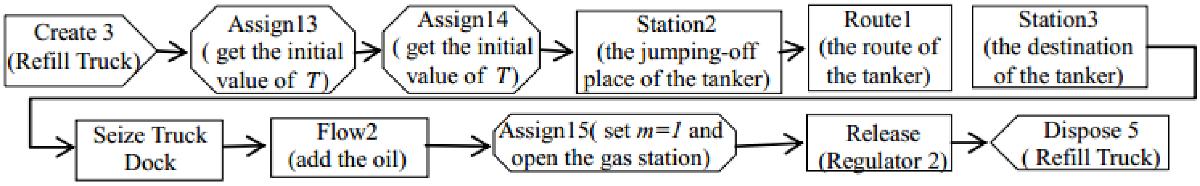

FIGURE 4. The simulation of oil tankers

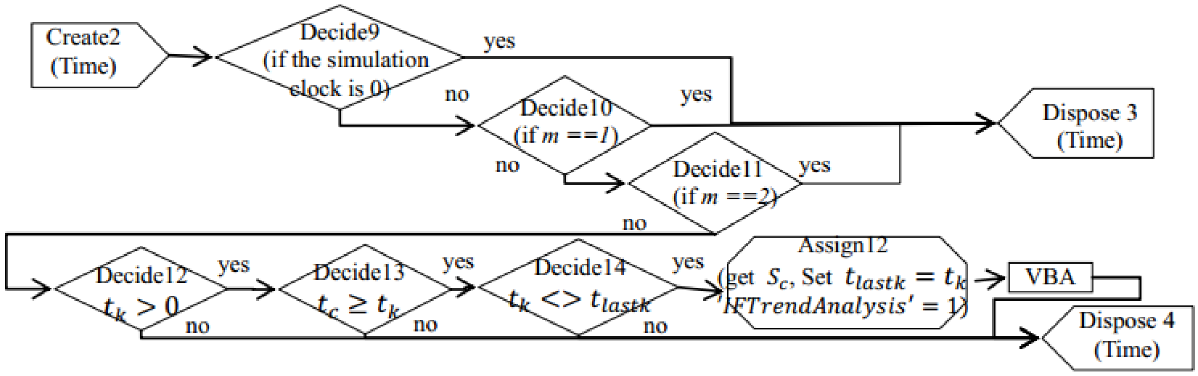

FIGURE 5. The simulation of time event

we mainly define the values of the parameters, such as $t_{\min}$, and $v_{\max}$. Especially, we set the parameter $IFTrendAnalysis = \begin{cases} 0 \ (SafePoint(t_{\min} \geq T)) \\ 1 \ (PossiblyAbornormalPoint(t_a)) \\ 11 \ (PossiblyAbornormalPoint(t_a)) \end{cases}$ to represent the needed time points. In the simulation process of the cars' arrival, when the time is up to t_k, we set the parameter *IFTrendAnalysis* as 1 at the possibly abnormal time point. However, we simulate the whole flow in the discrete-event simulation system, only the event of car coming can drive the simulation process, which could lead to the time far greater than t_k. Thus, besides the car coming event-driven simulation, we also simulate the time event by every half minute, in which case when the time is up to t_k, we can perceive the point timely and set the parameter *IFTrendAnalysis* as 11. When $t_{\min} \geq T$, there is no stockout event before the tanker arrives at the gas station and we set the parameter *IFTrendAnalysis* as 0.

6) Delay Module, it can delay the flow of the entity in the model in a certain period of time. In this paper, it mainly simulates the preparation time before oiling and the pay time after oiling.

7) Dispose Module, it simulates the leaving of an entity.

4.2. **Analysis of the results.** We detect whether we can achieve the whole flow successfully under two different parameter groups, including the distribution of the arrival time interval of car – A, the distribution of oiling time – B, the amount oil of the cars – C, the original stock of the gas station – S_0, the distribution of the arrival time interval of tankers – D, the safe stock – S_s and the original travel time between the current location of the tanker and the gas station – T_0.

The first parameter group is as follows: $A = 0.999 + GAMM(62.6, 0.814)$s, $B = TRIA(2,3,4)$min, $C = TRIA(20,30,40)$L, $D = UNIF(12.75, 13.25)$h, $S_0 = 200$, $S_s = 120$L, $T_0 = 2$h.

The results in Table 1 and Table 2 show that we can successfully achieve the whole flow of the real-time rolling approach depicted by Figure 2 in Section 3.2. Table 1 shows

TABLE 1. The update of the parameters

k	v_0	S_c	$t_{\min}$	T	t_k	t_0
1	10	200.00	2.00	119.30	8.70	0.70
2	20	191.54	1.79	118.45	5.12	1.55
3	20	129.05	0.23	113.98	6.48	6.02
4	30	119.47	−0.01	113.50	6.48	6.50
5	40	115.81	−0.10	113.38	6.52	6.62
6	40	54.20	−1.64	111.71	6.64	8.29
7	40	29.33	−2.27	110.96	6.77	9.04
8	30	0.07	−3.00	110.03	5.97	9.97
9	40	2000.00	47.00	1739.00	168.00	121.00
10	30	466.89	8.67	1689.88	181.68	170.12
11	40	436.48	7.91	1688.77	179.14	171.23
12	30	244.69	3.12	1680.75	183.41	179.25
13	40	234.41	2.86	1680.41	182.45	179.59
14	40	129.22	0.23	1677.40	182.83	182.60
15	40	109.43	−0.26	1676.78	182.95	183.22
16	30	85.54	−0.86	1675.97	182.88	184.03
17	40	81.04	−0.97	1675.82	183.20	184.18
18	40	2000.00	47.00	1739.00	941.78	894.78
19	20	438.52	7.96	1691.42	958.29	942.36
20	30	436.49	7.91	1691.31	953.01	942.46
21	40	419.39	7.48	1690.74	950.52	943.03
22	40	147.13	0.68	1682.94	951.52	950.84
23	30	95.74	−0.61	1681.51	951.46	952.27
24	40	82.82	−0.93	1681.08	951.77	952.70
25	40	61.61	−1.46	1680.42	951.89	953.35
26	40	38.31	−2.04	1679.72	952.02	954.06

that when $v_{t_c} > v_0$, the parameters are updated. For example, from $k = 1$ to $k = 2$, the corresponding v_0 is updated from 10 to 20. When the tanker arrives at the gas station, the parameters are updated. For example, when $k = 9$, the current stock of the gas station is 2000, which verifies that the tanker just finished the unloading of the oil. When the possibly abnormal point is detected, the parameters are updated. For example, from $k = 7$ to $k = 8$, although v_0 is updated from 40 to 30, $t = 9.04$ is the possibly abnormal point, and the parameters are updated.

Table 2 shows that when the parameter *IFTrendAnalysis* is 1 or 11, there are the possibly abnormal time points $t_a = t_c$ and $t_c \geq t_k$.

The second parameter group is as follows: $A = \mathit{expo}(1.5)$ min, $B = \mathit{TRIA}(2, 3, 4)$ min, $C = \mathit{TRIA}(20, 30, 40)$L, $D = \mathit{UNIF}(22.75, 23.25)$h, $S_0 = 2000$, $S_s = 120$L, $T_0 = 0.5$h. The results in Table 3 and Table 4 also indicate that we successfully achieve the whole flow.

In Table 4, the parameters are not updated from $t_0 = 0.7$ to $t_0 = 31.84$ which is caused by the occurrence of no stockout event and then it is unnecessary to continue the perceiving of the possibly abnormal points. When $v_{t_c} > v_0$, the parameters are updated. For example, from $k = 2$ to $k = 3$, the corresponding v_0 is updated from 10 to 20. When the tanker arrives at the gas station, the parameters are updated. For example, when $k = 2$, the current stock of the gas station is 2000, which also verifies that the tanker just finished the unloading of the oil. When the possibly abnormal point is detected, the parameters are updated. For example, from $k = 9$ to $k = 10$, although v_0 is updated from 40 to 10, $t = 110$ is the possibly abnormal point, and the parameters are updated.

TABLE 2. The possibly abnormal points and the safe points

t_c	*IFTrendAnalysis*	t_k	k	t_c	*IFTrendAnalysis*	t_k	k
5.20	11.00	5.12	2	182.50	11.00	182.45	13
6.50	11.00	6.48	3	182.90	11.00	182.83	14
6.50	1.00	6.48	4	183.22	1.00	182.95	15
6.62	1.00	6.52	5	184.03	1.00	182.88	16
8.29	1.00	6.64	6	184.18	1.00	183.20	17
9.04	1.00	6.77	7	941.80	11.00	941.78	18
9.97	1.00	5.97	8	950.60	11.00	950.52	21
168.10	11.00	168.00	9	951.60	11.00	951.52	22
179.20	11.00	179.14	11	952.27	1.00	951.46	23

TABLE 3. The arrival time of the tanker

The arrival time of the tanker	The current stock of the gas station when the tanker arrives at the gas station	The arrival time of the tanker	The current stock of the gas station when the tanker arrives at the gas station
120.00	0.00	893.78	0.00

TABLE 4. The update of the parameters

k	v_0	S_c	$t_{\min}$	T	t_k	t_0
1	10	2000.00	47.00	29.30	188.70	0.70
2	10	2000.00	47.00	1738.15	219.85	31.85
3	20	1991.05	46.78	1737.26	126.30	32.74
4	30	1988.40	46.71	1737.12	95.16	32.88
5	40	1971.02	46.28	1736.55	79.73	33.46
6	10	1058.69	23.47	1684.18	179.68	85.82
7	20	1053.81	23.35	1683.70	132.99	86.30
8	30	1048.09	23.20	1683.41	117.53	86.59
9	40	1033.29	22.83	1682.92	109.92	87.08
10	10	535.31	10.38	1657.97	153.56	112.03
11	20	535.12	10.38	1657.95	132.81	112.05
12	30	495.19	9.38	1655.95	126.55	114.05
13	40	327.53	5.19	1644.07	131.12	125.93
14	40	141.63	0.54	1638.80	131.75	131.20
15	20	104.71	−0.38	1637.10	132.14	132.90
16	10	67.03	−1.32	1633.92	130.79	136.08
17	20	56.57	−1.59	1632.87	133.96	137.13
18	10	16.36	−2.59	1630.38	129.26	139.62
19	20	12.36	−2.69	1629.98	134.64	140.02
20	10	2000.00	47.00	1738.20	1593.58	1405.58
21	20	1983.09	46.58	1736.51	1500.42	1407.27
22	30	1982.26	46.56	1736.47	1469.38	1407.31
23	40	1964.08	46.10	1735.86	1454.02	1407.92

Table 5. The possibly abnormal points and the safe points

t_c	*IFTrendAnalysis*	t_k	k	t_c	*IFTrendAnalysis*	t_k	k
0.7	0	188.70	1	132.90	1	132.14	15
79.8	11	79.73	5	136.08	1	130.79	16
110.0	11	109.92	9	137.13	1	133.96	17
131.2	11	131.12	13	139.62	1	129.26	18
131.8	11	131.75	14	140.02	1	134.64	19

Table 6. The arrival time of the tanker

The arrival time of the tanker	The current stock of the gas station when the tanker arrives at the gas station
30.00	1373.35
1403.78	0.00
2782.89	0.00

In Table 5, when *IFTrendAnalysis* is 0, there is no stockout event before the tanker arrives at the gas station and there are no possibly abnormal points. We can get $t_{\min} = 47 > T = 29.3$ at $k = 1$ from Table 4, thus it can fulfill the flow and the stock of the gas station is $1373.35 > S_s$ when the tanker arrives at the gas station which can verify there is no stockout event before the arrival of the tanker. When *IFTrendAnalysis* is 1 or 11, there are the possibly abnormal points $t_a = t_c$ and $t_c \geq t_k$.

In Table 6, we get the arrival time of the tanker and the current stock of the gas station when the tanker arrives at the gas station by simulating the driving of the oil tanker.

The result and the above analysis of the simulations show that the proposed approach can perceive all the possibly abnormal time points, t_a, in real time.

5. **Conclusions.** At gas stations, it is hard to capture the abnormal consumption timely to avoid the occurrence of stockout due to the stochastic arrivals of demands. In this paper, a real-time rolling approach to perceiving the possibly abnormal time points of oil consumption is developed by excluding the strictly secure periods. The approach proposed in this paper integrates dynamic contexts, current states and future contexts to support real-time perceiving of possibly abnormal time points. From the theoretical perspective, the real-time rolling approach can capture all the possibly abnormal points by considering all interrelated and dynamic context. It supplements and deepens the methodology of the traditional online context anomaly detection that only process online data without considering the temporal dynamics of the context. It provides a new way of perceiving the possibly abnormal points in the area of online security monitoring. From the practical perspective, the proposed approach achieves the goal of perceiving the time point of possibly abnormal consumption of oil in real time. At this time point, the trend analysis of the oil consumption should be triggered in order to determine whether the possibly abnormal consumption will evolve to be a real one with the subsequent context. If a real anomaly is confirmed, a warning will be issued, which is important for keeping safety stock levels in the whole oil logistics system. Therefore, further research will focus on the future trend analysis of the oil consumption, which aims to analyze the consumption trend at the perceived time point in order to find out whether the possibly abnormal consumption will eventually evolve to be the real one. If it is, a warning should be issued to alert decision makers to take measures on time.

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