An Accountable Anonymous Data Aggregation Scheme for Internet of Things

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Abstract—The Internet of Things (IoT) has become increasingly popular in people’s daily lives. The pervasive IoT devices are encouraged to share data with each other in order to better serve the users. However, users are reluctant to share sensitive data due to privacy concerns. In this paper, we study the anonymous data aggregation for the IoT system, in which the IoT company servers, though not fully trustworthy, are used to assist the aggregation. We propose an efficient and accountable aggregation scheme that can preserve the data anonymity. We analyze the communication and computation overheads of the proposed scheme, and evaluate the total execution time and the per-user communication overhead with extensive simulations. The results show that our scheme is more efficient than the previous peer-shuffle protocol, especially for data aggregation from multiple providers.

Index Terms—Data aggregation; anonymous; accountable; IoT

I. INTRODUCTION

Data aggregation is a common task in modern computing systems, such as crowd-sourcing, sensor networks, and cloud computing. However, users are concerned with the privacy of sensitive data, such as medical records, or data that is geotemporal tagged. To motivate the user’s active involvement, many anonymous data aggregation schemes have been proposed to preserve data privacy. Threats that may expose the data ownership include the untrusted aggregator, unsecured channels and colluding adversarial participants. The receiver of a packet, like the data collector or an intermediate processor, is capable of tracing back to its immediate sender (e.g., via the source IP address). To preserve data anonymity, the aggregation protocol must break the link between a piece of data and its originator (not necessarily the immediate sender).

Existing anonymous data aggregation mechanisms are designed for the traditional server-client architecture, in which a set of users (clients) submit their data to the collector (server). However, it is meaningless to discuss data anonymity for the simple server-client data aggregation in IoT ecosystem. In IoT scenario, each IoT company is viewed as the combination of its central server, and a set of client devices deployed with users. The client devices are the actual generators of data, and provide data readings to their owners. However, client devices are manufactured by the respective IoT companies, and users do not have the control to prevent the data from being secretly sent to the IoT company server in the background. Therefore, instead of studying the anonymity of data aggregation from the IoT devices of an individual company, we focus on data aggregation across multiple IoT companies. This problem can be described using a server-clients-servers framework (shown in Figure 1), in which multiple client IoT devices are deployed within a home environment. One IoT company (collector server) wants to collect a group of data produced by the client devices of other IoT companies for aggregation studies. For example, a smart home solution company may anonymously collect and analyze the energy consumption and generation data from the residents of a neighborhood, to devise better planning for both energy suppliers and home owners. The major difference to the traditional data aggregation is that the collector requires the data from multiple provider servers to be submitted as a group (tuple), while users need to prevent an IoT server (either the collector server or a provider server) from revealing the owner of the data which does not belong to that IoT company.

In this paper, we study the anonymous data aggregation across multiple providers in the IoT system. The adversaries considered include compromised users, malicious IoT servers, and a global passive eavesdropper. Two passive collusion attacks and 12 active attacks are presented. We design a robust, efficient and accountable aggregation scheme that is resistant to all types of manipulations and collusions by the adversarial entities. We analyze how our scheme can defeat these attacks and provide the accountability, as well as its communication

Fig. 1. The System Architecture
and computation overheads. The performance is evaluated via simulation tests, and is compared with the Dissent protocol [6]. The results indicate that our scheme is more efficient when collecting data from multiple providers.

Our main contributions are listed as follows:

- To the best of our knowledge, this is the first work that studies the anonymous data aggregation across multiple IoT companies in the server-users-servers architecture of the IoT system, which cannot be properly solved by existing solutions that focus on the traditional server-users structure.
- Our aggregation scheme does not rely on any trusted 3rd-party server. Instead, it takes advantage of the semi-trustworthy provider servers, considering an IoT company will not leak the data produced by its own client devices to other companies.
- We consider a more complex adversary model. Two advanced passive collusion attacks and twelve active attacks specific to our scheme are presented.
- We analyze the communication and computation overheads, and measure the execution time and the per-user communication overhead with extensive simulations.

II. RELATED WORK

The existing data aggregation schemes can be generally classified into two categories: (1) the collector only knows the originator of each encrypted message, but cannot directly decrypt any of the individual messages. Instead, the plaintext is derived through a collaborative computation over a set of ciphertexts, in which the collector cannot figure out the actual contributors of the plaintext data. (2) the collector receives unencrypted messages that contain the plaintext data, but the immediate sender of each message is not the originator. This happens when the packets have been routed through a set of relays or have been randomly shuffled.

The first class of methodologies include DC-nets [4] and \( (t; N) \)-secret sharing based scheme [25]. DC-nets utilize pairwise secrets to conceal the originator of data. However, there are two major problems in DC-nets: (i) only one member can embed her data into the ciphertext per slot, while all other members still have to perform the XOR operations (ii) pairwise shared secret keys are required between every two members, and the secrets have to be updated every slot. The generation and distribution of the pairwise secrets can be a heavy burden, especially when there is a large number of members. In [25], one user can divide her secret \( s \) into \( N \) shares and submitted by \( N \) users separately. However, only one user can submit per slot while all others have to generate and share \( N \) shares of fake data, which brings large communication overhead.

The second class of aggregation schemes consists of Mix-Net [3], onion routing [19] [8], and peer-shuffle based approach [2]. Mix-Net offers anonymity by relaying encrypted messages through a chain of proxy servers (mixes), which take turns to perform decryption, shuffle, and re-ordering on the messages. In onion networks, the encrypted message is transmitted along a path of pre-selected onion routers, each peels away one layer of encryption and uncovers the successor router. However, both Mix-Net and early onion routing systems all require reliable and trustful 3rd-party proxies/routers, which may not be available in practice. The evolved onion routing based systems propose peer-forwarding strategy [20], in which users themselves serve as the relay for each other. However, the predecessor of the first collider has a greater chance to be the data originator than other honest users, and this scheme is unable to defend against traffic analysis attacks launched by a global eavesdropper. RAC protocol [17] solves these issues by enforcing periodical broadcasts for all users, which bring in huge communication overheads.

The peer-shuffle based approach [2] requires each member to perform shuffle and one layer of decryption on the messages that have been encrypted with all members’ public keys. Dissent [6] enhances this protocol to offer accountability against traffic analysis and compromised members. Then, in order to reduce the heavy computation overheads, many of the above schemes have been modified to be more scalable. Two types of techniques are commonly used. The first type is to gain better scalability while sacrificing anonymity (e.g. reducing anonymity set) [14] [1]. The second type utilizes trusted 3rd-party servers to offload the communication and computation overheads [8], [7], [21]. Instead, our scheme preserves the maximal anonymity, and does not utilize the assistance of the trustworthy external 3rd-party servers.

A recent work [24] studies the anonymous data reporting for participatory sensing in IoT. They adopt the peer-shuffle for slot reservation and pairwise secret XOR for data submission. They still consider data aggregation in the traditional single server-clients structure, which as we have explained, is not a practical issue in IoT system. They do not consider the accountability for attacks and misbehaviors either.

Key management [9], [11], [23] is essential for security. Several papers [10], [12], [15], [16], [22] have studied related security issues.

III. DATA AGGREGATION IN IoT

A. Motivation

Aggregate study is a typical application of anonymous data aggregation. In IoT context, one IoT company may need to collect the data of other IoT companies along with its own data, from a certain group of users. By analyzing the patterns and correlations of these data, e.g. using data mining techniques, the collector company can gain better understanding of its data and product. In general, an aggregate study is not a strict real-time task, instead it is conducted with a relatively high frequency and over a long period of time. This means that the aggregation can bear rather longer elapse caused by computations, but require low communication overhead. Furthermore, since users may not trust either the IoT company servers or a 3rd-party server, the anonymity is achieved via user cooperations only. The IoT provider servers may assist the data submission, but only for improving efficiency. Hence, we adopt a modified version of peer-shuffle technique in our scheme. The peer-shuffle can
provide anonymity for the messages/data of honest users if no more than \( n - 2 \) out of the \( n \) users collude. In fact, all sorts of anonymizations based on peer collaboration will fail if \( n - 1 \) users are compromised, so we assume at least two users are honest. Moreover, considering various adversaries may try to break the data privacy or tamper the data submission, the scheme must be accountable for attacks and misbehaviors.

### B. The System Model

Our system model consists of a set of IoT companies \( W = \{W_0, W_1, ..., W_m\} \) and a set of users \( U = \{U_1, U_2, ..., U_n\} \). An IoT company \( W_i \) includes a central server \( S_i \) and a number of affiliated client devices \( A_{ij} \) (owned by user \( U_j, 1 \leq j \leq n \)). We use \( S_0 \) to denote the data collecting server (collector server), and the rest of the servers \( S_1, S_2, ..., S_m \) are the data providing servers (provider servers). All servers maintain connections with the affiliated client devices. Each user \( U_j \) is also connected to all IoT client devices in his/her home, \( A_{ij}(0 \leq i \leq m) \), through a management device (e.g. smartphone). The management device has access to the data generated by IoT devices, and will perform the heavy computations for data anonymization. Without loss of generality, we assume that every user owns exactly one client device from each IoT company. The data reading \( D_{ij} \) of device \( A_{ij} \) is accessible by both its owner \( U_j \) and the server \( S_i \). Additionally, data generated by the same type of client devices (i.e., belonging to the same IoT company) are of the same format and length. The collector company \( W_0 \) can aggregate data \( D_{ij} \) from multiple provider companies \( W_i(1 \leq i \leq m) \), if approved by the data owners \( U_j \). Figure 1 illustrates the many-to-one data aggregation in the server-users-servers architecture.

Each IoT company \( W_i(0 \leq i \leq m) \) owns a pair of public/private keys \((KU_i, KR_i)\). Each user \( U_j(1 \leq j \leq n) \) also possesses a public/private key pair \((KU_j, KR_j)\). Given a plaintext \( M \) and the public key \( KU \), the encryption also takes some random bits \( R \) as input. The produced ciphertext is expressed as \( C = E_{KU}[M] \). The plaintext can be recovered with the private key \( KR \) (if not required), \( M = D_{KR}[C] \). The advantages of introducing random bits are two-fold: (1) the same piece of plaintext can generate different ciphertexts, so that the equality of data will not be exposed after encryption; (2) the recovery of encrypted data from the decrypted data is disabled. Various probabilistic encryption methods can achieve these characteristics, such as the Elgamal encryption algorithm and the plaintext expansion/padding. In peer-shuffle process, the plaintext messages need to be encrypted with all users’ public keys (i.e., serial encryptions). For the Elgamal encryption algorithm, the ciphertext length may increase exponentially to the total number of encryption rounds \( N \). In contrast, the padding approach can maintain a ciphertext length of \(|M| + O(N)\), which is a linear increase. The plaintext padding can simply extend the plaintext in a predefined format (e.g. \( \{R || M\} \)), or use more advanced and secure schemes like Optimal Asymmetric Encryption Padding (OAEP) [18].

We choose the OAEP for plaintext padding in our scheme. The expression of serial encryptions is abbreviated as

\[
E_{KU_i; KR_i}[M] = E_{KU_0}[E_{KU_1}[E_{KU_2}[...[E_{KU_m}[M]]...]]
\]

Besides, each IoT company \( W_i(0 \leq i \leq m) \) has another pair of signing/verification keys \((KS_i^0, KV_i^0)\) to sign a message \( M \) as \( \{M|SIG_{KS_i^0} = [M] \} \) and verify a signature \( sig \) as \( V_{F_{KV_i^0}}[sig] \). Similarly, each user \( U_j(1 \leq j \leq n) \) also has the key pair \((KU_j^0, KV_j^0)\) for signature generation and verification. We define \( \{M|SIG_{KS} \) as the concatenation (“||”) of message \( M \) and its signature (signed by key \( KS \))

\[
\{M|SIG_{KS} = M || SING_{KS}[M]
\]

The hash value of a message \( M \) is denoted as \( Hash[M] \). The permutation function \( p(z) \) randomly shuffles a group of objects, and assigns a new position for the \( z \)th object. The pseudorandom function \( PRF(L, seed) \) is used to generate the most significant \( L \) bits from \( seed \). The random numbers used in encryptions can be generated using this function.

### C. Referenced Data Aggregation

To perform an aggregate study, the collector server needs to gather a set of data from the users of interest. For user \( U_{ij} \), the data to be submitted includes the readings of all provider companies’ devices (provider data). We define this set of data as the provider data set \( P_j = \{D_{ij}\}, 1 \leq i \leq m \). The provider data set \( P_j \) and the reading of the collector company’s device (collector data) compose a data tuple \( T_j, T_j = \{D_{0j}, P_j\} \). The traditional data aggregation is one-dimensional, hence users only submit their independent pieces of data. However, the data aggregation in the IoT is two-dimensional. Each user \( U_{ij} \) needs to submit the provider data set \( P_i \), which is referenced by the collector data \( D_{0j} \). Since the collector server knows \( D_{0j} \) for each user, it can find the owner of data tuple \( T_j \) if the \( D_{0j} \) is unique among all users. Hence, it should avoid collecting from a user with unique \( D_{0j} \), for example, by splitting the data range into small segments and rounding \( D_{0j} \) values up/down to the nearest segment.

Another characteristic in IoT data aggregation is the provider servers. Although they are not fully reliable, our scheme takes advantage of these provider servers to delegate the submission of their own data. If users submit the provider data set by themselves, they need to perform peer-shuffle on the data in order to prevent being traced by the collector. All such efforts can be saved if each corresponding provider server submits the provider data for its users.

Besides, considering that the receiver may get an updated data reading by the time the request arrives (which is not the data intended by the requester), we need to solve the inconsistency caused by the elapse of message transmissions. Specifically, the data \( D_{0j} \) is embedded in the aggregation request sent to users, and the data \( D_{ij} \) is embedded in the submission request sent to provider servers.
D. The Adversary Model

1) IoT Companies and Users: All IoT companies and users are dedicated to preserving the privacy of their own data, meanwhile they are curious about other’s data. We assume that all IoT companies will obey the commitment not to disclose their user’s data without permission, so the IoT company that deliberately reveal or trade data to other IoT companies is not considered within the scope of this paper. Additionally, the client devices are the source of data, and they will always provide the true data to their owners and the corresponding company servers. However, malicious users and provider servers may deviate from the protocol. We consider two basic adversarial actions: collusion and manipulation. Collusion means that some compromised users may cooperate with each other or with the collector/provider server to de-anonymize the data of honest users. Manipulation allows servers and users to insert, delete or tamper the messages handled by them.

2) Eavesdropper: A global and passive eavesdropper may exist, which can monitor all traffics in the network. It may collude with an IoT server and malicious users.

IV. THE PROPOSED SCHEME

In this section, we present the proposed accountable anonymous data aggregation scheme. The scheme works in 6 phases, $\sigma$ is the phase ID. The message transmitted in phase $\sigma$ is denoted by $\Omega_\sigma$. Each run of data aggregation is uniquely identified by the session ID $sid$. To hold the server and user behaviors accountable, the messages they transmit in each phase are associated with the session ID $sid$ and phase ID $\sigma$, and are signed with the sender’s signing key. The receivers will first verify the signature of the received messages before further processing. All transmitted and received messages as well as the random numbers used for encryptions are recorded until the next protocol run, to serve as the evidence in case an investigation of misbehaviors is conducted.

A. The Data Aggregation Protocol

Phase 1: Aggregation requests

The aggregation begins at the collector server $S_0$, who sends the aggregation requests for data $D_{0j}(1 \leq i \leq m)$ to each user $U_j$. The request message contains the collector data $D_{0j}$, and it is encrypted with $U_j$’s public key $KU^U_j$ and the random number $R_{0j}$ selected by the collector server.

$$\Omega_1 = \{E_{KU^U_j}[D_{0j}], sid, \sigma_1\}SIG_{KS^U_0}$$

Phase 2: Submission of index messages

Upon receiving the aggregation request, each user $U_j$ prepares a pair of information: the collector data $D_{0j}$ and a pseudonym number $PN_j$ (as the index number). $PN_j$ is an $L$-bit random number generated using $PRF(L, seed_j)$, where $seed_j$ is randomly selected by $U_j$. The probability that no collision occurs among the selected index numbers is $L$ is selected to limit the collision probability under a sufficient small threshold (e.g., $10^{-3}$). The data $D_{0j}$ and index number $PN_j$ pair is defined as the index message (IM) of $U_j$.

$$IM_j = \langle D_{0j}, PN_j \rangle$$

Then, the index message $IM_j$ is encrypted using the public keys of all users, following a given order (e.g. sequential order). For illustration, here we conduct the serial encryptions in the order $U_1, ..., U_n$ The encrypted index message (EIM) is

$$EIM_j = E_{KU^U_{01}}^{R_{01}^j} \cdot ... \cdot E_{KU^U_{n}}^{R_{nj}^j}[IM_j]$$

where $R_{0j}^1, ..., R_{nj}^j$ are the random numbers selected by $U_j$ for the encryptions with public keys $KU^U_1, ..., KU^U_n$, respectively. All encrypted index messages are sent to the first processor for individual anonymization processing (IAP).

$$\Omega_2 = \{EIM_j, sid, \sigma_2\}SIG_{KS^U_j}$$

Phase 3: Anonymization of index messages

The data anonymization is achieved via the IAPs by each user (processor), performed in the reverse order of the serial encryptions. Before the processors begin the IAP process, they need to make sure that all EIMs are valid: their received EIMs have been properly handled without being “marked”. For these purposes, each processor carries out the replication attack checking (Section IV-A1). In our example, the first processor is the last encryptor $U_n$. The received EIMs are concatenated as an anonymization bundle message (ABM),

$$ABM_n = EIM_1 \| ... \| EIM_n$$

The EIMs can be in any order (e.g., the order they arrive at the processor). For simplicity, here we list them sequentially. The IAP process contains two steps: shuffle and decryption. User $U_n$ first shuffles the EIMs with its random permutation function $p_n$.

$$ABM_n \xrightarrow{\text{shuffle}_{p_n}} EIM_{p_n(1)} \| ... \| EIM_{p_n(n)}$$

Then $U_n$ decrypts all pieces of EIMs with her private key $KR^U_n$. When the IAP finishes, the ABM becomes

$$ABM'_n = D_{KR^U_n}[EIM_{p_n(1)}] \| ... \| D_{KR^U_n}[EIM_{p_n(n)}]$$

As all other users repeat the IAP (i.e., each shuffles the EIMs and strips off one layer of encryption), the last processor (i.e., $U_1$) will be able to recover the original index messages in a new random order.

$$ABM'_1 = IM_{p(1)} \| ... \| IM_{p(n)}$$

where $p$ stands for a series of permutations $p_1, ..., p_n$ made by each processor. The recovered index messages are broadcasted to all users as well as the collector server $S_0$. In phase 3, the transmitted messages are the resulted $ABM'$ after each IAP,

$$\Omega_3 = \{ABM', sid, \sigma_3\}SIG_{KS}$$

where $KS$ is the signing key of the corresponding processor.

Phase 4: Peer-shuffle verification and submission requests

At the start of phase 4, all users first run the replacement attack checking (Section IV-A2) and the broadcast consistence
checking (Section IV-A3), to verify the consistency of the broadcasted final ABM and confirm the existence of their own index messages. Then, the uniqueness checking (Section IV-A4) is performed to check the existence of unique $D_{ij}$ or identical index numbers among IMs. After these checkings are passed, each user $U_j$ informs the provider servers $S_i (1 \leq i \leq m)$ to submit the data $D_{ij}$ to the collector for them. Specifically, $U_j$ prepares a data submission message $DSM_{ij}$ which contains the data $D_{ij}$ and the index number $PN_j$. The index number is encrypted using the collector’s public key $KU_i^S$ and a random number $R_j$. The submission message $DSM_{ij}$ is expressed as

$$DSM_{ij} = < D_{ij}, E_{KU_i^S}[PN_j]>$$

Finally, the data submission message is encrypted using the provider server’s public key $KU_i^S$ and another random number $R_j$, and sent to the provider server $S_i$.

$$\Omega_{4.2} = \{ E_{KU_i^S}[DSM_{ij}], sid, \sigma_{4.2} \}SIG_{KS_j}$$

**Phase 5: Data submission**

After receiving the data submission messages from users, provider servers will submit them to the collector altogether. For a given provider server $S_i (1 \leq i \leq m)$, the data of all its users are submitted as

$$\Omega_5 = \{ DSM_{i1} || ... || DSM_{in}, sid, \sigma_5 \}SIG_{KS_i}$$

**Phase 6: Data submission verification**

The collector server receives the aggregated data tuples in two separate parts: the first part is the $< D_{0j}, PN_j >$ pair (received by the end of phase 3) and the second part is the $< D_{ij}, E_{KU_i^S}[PN_j] >$ pairs. It first decrypts each $E_{KU_i^S}[PN_j]$ with its private key $KR_i^S$. Then, the original data tuple $D_{ij}$ can be reconstructed by linking the $< D_{0j}, PN_j >$ and $< PN_j, D_{ij} >$ pairs via the unique index number $PN_j$. The data submission checking (Section IV-A5) must be performed by each user, in case the provider servers may have manipulated the submitted data or the index number. The collector server will finally accept the provider data if the checking is passed.

**List of Checkings:**

1) **Replication Attack Checking:** each processor scans all EIMs, and checks if any two are duplicated or have the same encrypted index number. With extremely low probability, the duplication can be caused by the collision during the index number generation when their owners select the same random numbers for serial encryptions. This can be confirmed by replaying the IAP processes backwards (i.e., re-encrypting the index messages layer-by-layer with corresponding public keys and logged random numbers), and then comparing with the logged original EIMs. We only focus on whether the reconstructed EIMs exist in the logged messages, while the permutations are not replayed. If the duplication is indeed due to the collision, the aggregation procedure will be restarted. Otherwise, it must be a replication attack (Attack 7) launched by compromised processor(s): the aggregation procedure is aborted, and an investigation is launched to replay the executed IAP processes. The detection for a replication attack has to be conducted at each processor, otherwise the malicious processors may bypass the checking by changing the replicated EIMs back to the original ones which are owned by themselves.

2) **Replacement Attack Checking:** each user scans all recovered index messages in the broadcasted final ABM, and confirms the existence of its own index message. If it is missing, there must be malicious processor(s) who have replaced its EIM (Attack 8). The aggregation procedure is aborted, and the investigation to find the manipulator is launched by replaying the IAP processes. Note that malicious processors cannot recover the replaced legitimate EIMs of honest users once they have been processed by an honest processor, as they know neither the honest processor’s private key nor the random numbers used by the honest users.

3) **Broadcast Consistence Checking:** all users as well as the collector server must verify that the broadcasted final ABMs $ABM_f$ they received are consistent. Since the broadcast is not in a wireless channel, all receivers have to explicitly exchange and compare the received $ABM_f$. To make it more efficient, they may only exchange the hash value $Hash[ABM_f]$.

$$\Omega_{4.1} = \{ Hash[ABM_f], sid, \sigma_{4.1} \}SIG_{KS}$$

where $KS$ is the signing key of the broadcast receiver. The hash values are compared by each receiver. If any of them is different from others, the last processor must have launched the broadcast attack (Attack 9). The aggregation is aborted.

4) **Uniqueness Checking:** The uniqueness checking on shuffled index messages consists of two parts. In the first part, each user checks if its $D_{0j}$ is unique among all IMs. If so, the collector has launched a unique collector data attack (Attack 10). In the second part, each user checks if its index number $PN_j$ is not unique among all IMs. If so, it can be due to the coincidence of index number selection, or the manipulation made by the previous IAP processor who has intentionally replicated an honest user’s encrypted index number (not necessarily the data part). Since this is similar to the replication attack checking, it can be handled in the same way and we do not categorize it as an independent attack.

5) **Data Submission Checking:** each user needs to ensure that their DSMs have been correctly submitted by the provider servers, who may have tampered with the data $D_{ij}$ and/or the encrypted index number $E_{KU_i^S}[PN_j]$ (Attack 11). This requires the cooperation of the collector server, who will acknowledge each submission by replying with the signed DSM to the respective provider server $S_i$.

$$\Omega_{6.1} = \{ DSM_{ij}, sid, \sigma_{6.1} \}SIG_{KS_i^S}$$

After all the acknowledgement messages have arrived at the provider servers, each of them sends the signatures of the acknowledgement messages, to the respective user who owns the unique DSM$_{ij}$ (i.e., the unique $E_{KU_i^S}[PN_j]$).

$$\Omega_{6.2} = \{ E_{KU_i^S}[SIG_{KS_i^S}[DSM_{ij}]], sid, \sigma_{6.2} \}SIG_{KS_i^S}$$
We present 4 types of active attacks specific to our scheme, including the disruption attacks, data inference attacks, and data falsification attacks.

1) Disruption Attacks: The disruption attacks abort the protocol run by creating an abnormality that it cannot handle. An investigation is conducted immediately when such abnormality happens. Next, we list the possible disruption attacks launched by the processors and provider servers, separately.

User (processor):
- Attack 1: the malicious user encrypts the index message using the wrong public key(s), or signs the transmitted messages using wrong signing key.
- Attack 2: the malicious user doesn’t send its EIM, or sends multiple EIMs to the first IAP processor.
- Attack 3: the malicious IAP processor illegally inserts or deletes EIM(s) during its processing.
- Attack 4: the malicious user doesn’t send its DSM, or sends multiple DSMs to the same provider server.

Provider server:
- Attack 5: the provider server encrypts the DSM to be submitted with the wrong public key or its signature is generated with the wrong signing key. It may also happen that the provider server tampers the signed acknowledgement message of the collector.
- Attack 6: the provider server doesn’t submit the DSM, or submits multiple copies of DSMs for a given user.

2) Data Inference Attacks: We present 4 types of active data inference attacks in which the attacker(s) manipulates the peer-shuffle process to expose the owner identity of the index message(s). From the attacker’s perspective, to break the strong anonymization provided by peer-shuffle, the target EIM has to be somehow “marked” so that it can be recognized even after it has been randomized by honest processors.

- Attack 7 (replication attack): the compromised users mark the target EIM by replicating other honest users’ EIMs (or only the encrypted index number part), so that the target EIM is unique among the honest users. As illustrated in Figure 2, the three original EIMs contain the index number 1, 2, 3, respectively. The first processor $U_1$ is compromised and it wants to reveal honest user $U_3$’s index number. It copies the other honest user $U_2$’s $EIM_2$ and overwrites its own $EIM_1$. Now, it is easy to tell the unique $EIM_3$ from the duplicated $EIM_2$ in the rest of IAP processes. In the end, the colluding party can obtain $U_3$’s specific index number when $EIM_3$ is fully decrypted. There are two prerequisites for a replication attack: (1) the first processor must be compromised so that the originator of the EIMs is known; (2) the number of compromised users must be no less than 1 compared to the number of honest users.

- Attack 8 (replacement attack): the compromised users mark the target EIM by replacing other honest users’ EIMs with the fake EIMs they created. The fake EIMs are different to the target EIM and their own EIMs. In a replacement attack, the colluding entities know exactly what the decrypted fake EIMs look like when they go through each honest processor. Therefore, the target EIM is the only one they do not recognize. As illustrated in Figure 3, the compromised processor $U_1$ wants to know honest user $U_3$’s index number. During its own IAP process, $U_1$ replaces the $EIM_2$ of the other honest user $U_2$ with a fake EIM. In all the rest IAP processes, $U_1$ can identify not only its own $EIM_1$, but also the fake $EIM_2$ it created. The only unrecognized EIM left would be the target. Eventually, the attackers can obtain the plaintext index number of $U_3$. There is one prerequisite for a replacement attack: the first processor is compromised.

- Attack 9 (broadcast attack): the last processor is supposed to broadcast the final ABM (i.e., permuted index messages) to all users and the collector server. However, it may infer the index number of honest users by sending them different (manipulated) ABMs. As illustrated in Figure 4, the last IAP processor $U_3$ is malicious while $U_1$ and $U_2$ are honest. The permutation function $p(j)$ calculates the permuted position of $U_j$’s index message. $U_3$ is not sure which honest user owns which piece of the two unrecognized index messages. Therefore, it creates two manipulated ABMs, each has one of the two unknown IMs replaced by the fake index message $IM_f$. This is similar to a guessing attack. If the guess is wrong, both
honest users will report that a replacement attack is detected. Otherwise, both of them find their IMs in the manipulated ABMs, and \( U_3 \) will know the belonging of the two index messages. The prerequisite of broadcast attack is that the last processor is malicious.

- Attack 10 (unique collector data attack): the collector server intentionally collects data from \( U_j \), whose collector data \( D_{0j} \) is unique among all users. As a result, its data tuple \( T_j \) can be identified by the collector server.

3) Data Falsification Attacks: The data submission messages can be manipulated by the attackers. Here, we consider pure data falsification attacks whose only purpose is to corrupt the aggregated data (provider data set \( P_j \)).

- Attack 11: the provider server tampers the DSMs when submitting to the collector server.

- Attack 12: the malicious user intentionally submits the wrong/falsified data to the collector through honest provider servers. This attack can be detected only if the collector has the ability to validate the aggregated data, hence its detection is not included in the protocol as a standard step.

V. Analysis

A. Correctness

When our scheme terminates, either all honest users have correctly submitted their data to the aggregator, or the scheme is aborted and the investigation is launched. In the first case, all proactive checkings have been passed successfully and the protocol has not been interrupted by any disruption attack. The replacement attack checking verifies that the index messages of honest users are in the final ABM. The replication attack checking, broadcast consistence checking and uniqueness checking ensure that the index messages have been correctly received by the collector, and their ownerships are not exposed due to replication marking, random guessing or collector data uniqueness. The data submission checking confirms that the data submission messages has been correctly submitted to the collector. Hence, the collector is able to reconstruct the data tuples by linking the index numbers. For the second case, the protocol is aborted by a disruption attack or because one of the checkings has failed.

B. Anonymity

Our privacy-preserving aggregation scheme is resistant to a variety of passive data inference attacks. If the proposed protocol is strictly followed, no entity (e.g., user, server, or the global eavesdropper) can passively infer any data that they are not supposed to know, either individually or collaboratively.

1) Collector server: users submit their data in two parts. The first part (index messages) is anonymized by peer-shuffle. The second part (data submission messages) is submitted via delegates (i.e., provider servers) as a batch. Hence for either of them, the collector server alone cannot trace to the owners.

2) Provider server: each provider server only has access to its own data, and cannot obtain other servers’ data by oneself.

3) Users: a user can access each other’s data in phase 3. However, peer-shuffle guarantees that the data of honest user will not be exposed unless there is only one honest user.

4) Passive collusion between the IoT server and users: the server (either collector or provider server) may collude with a number of compromised users, in order to infer the data that does not belong to the colluding entities. For collusion with the collector server, our scheme is based on peer-shuffle, which can guarantee data anonymity for honest users if there are at least two of them. For collusion with a provider server, the index number is encrypted with random bits in DSM to prevent the leak of collector data \( D_{0j} \) to the colluding party. Specifically, colluding users know the connection between \( PN_j \) and \( D_{0j} \) from the broadcasted IMs, while the provider server knows the owner identity of the encrypted index numbers \( E_{KU_j} [PN_j] \) from the received DSMs. The random number \( R_j \) must be used to break the equality after encryption, so that the colluding party cannot infer the \( D_{0j} \) value of honest users by linking the index numbers \( (KU_0^S) \) is publicly available).

5) Passive collusion involving a global eavesdropper: the passive eavesdropper is capable of monitoring the sender/receiver of all messages. In our scheme, messages are transmitted in phases, with the same length and format within each phase. So the traffic and timing analysis attack by the eavesdropper alone is mitigated. However, if it colludes with an entity that owns or can observe the plaintext contained in the encrypted messages, they may work together to de-anonymize the data or the index number in plaintext form. In phase 1, the eavesdropper may collude with the compromised users to infer the collector data \( D_{0j} \) (e.g. finding if any two are identical). In our scheme, \( D_{0j} \) is encrypted with random numbers selected by the collector, which breaks the equality in ciphertexts. In phase 2 and 3, the peer-shuffle can preserve the privacy of honest users (\( \geq 2 \)) since only each honest user themselves knows the random number used in the serial encryptions. In phase 4, the eavesdropper may collude with the collector server. Specifically, the eavesdropper knows the originator \( U_j \) of the encrypted DSMs \( E_{KU_i} [DSM_{ij}] \), while the collector server later gets \( DSM_{ij} \) from the provider \( S_i \). Although key \( KU_i^S \) is publicly available, the colluding party cannot associate the \( DSM_{ij} \) to the encrypted DSMs in \( \Omega_{4,2} \), as they do not know the random number \( R_j \). Message \( \Omega_5 \) and \( \Omega_{6,1} \) are transmitted between servers, so there is no individual user to track. The \( \Omega_{6,2} \) messages contain only the signatures, no data or index number can be exploited.

C. Accountability

Our scheme can preserve anonymity and provide accountability for the various active attacks launched by the collector, provider, compromised users or multiple colluding entities. If there are multiple attackers who cover for each other, at least one of them can be found. In general, the investigation is conducted in phases. For each phase, we only need to check if the output is correctly computed from the input message. While if there is an inconsistency with the message transmitted
between two entities, either the sender or the receiver is lying. The signed message can prove if the sender is the liar; otherwise, it is the receiver. The investigation may need to replay the IAP process. Note that the private keys are not required, the decryption process can be validated by replaying the serial encryptions in reverse using the public keys and the logged random numbers. Next, we present the detection and investigation for the 12 active attacks listed in Section IV-B.

The disruption attacks expose themselves as they break the current protocol run. Attacks 1 and 5 disrupt the protocol as the receiver of a message cannot successfully decrypt the message or when the signature cannot be verified. The failed decryption can be caused either by faulty encryption or someone has manipulated the message. Similarly, the wrong signature can be caused by either the incorrect signing process or from being tampered with. In such cases, the receiver only needs to prove that the problematic messages are indeed coming from the sender (i.e., signed with the sender’s signature); otherwise, the receiver is the one to blame. If the number of EIMs in phase 3 is not consistent with the number of participating users, the anonymization procedure will be replayed to check if it is due to illegal insertion/deletion by a malicious processor (Attack 3), or a malicious user who does not send or send multiple EIMs to the first processor (Attack 2). The first processor can trace the sender of each EIM, so it knows if anyone is supposed to submit the EIM while did not actually submit. The multiple submission of EIMs can be proved by the multiple signed $\Omega_2$ messages from the malicious user. The missing/extra DSM can be resulted from either a malicious provider server (Attack 6) or a malicious user (Attack 4). The signed $\Omega_4$ messages logged between the user and the provider server can prove which one is responsible for the data submission error.

The data inference attacks and the data falsification attacks are detected with a series of proactive checkings. The broadcast consistency checking, the uniqueness checking and the data submission checking, if failed, can immediately expose the attacker, which is the last processor (attack 9), the collector (attack 10), and a specific provider server (attack 11), respectively. The manipulator(s) of EIMs in the replication attack (Attack 7) and the replacement attack (Attack 8) can be found by replaying the IAP processes. For Attack 12, the investigation of the originator of the falsified data needs to check the specific signed $\Omega_4$ message in which it is contained. Note that our scheme can detect the data inference attacks and abort the protocol before any provider data is submitted. While for the data falsification attacks, the falsified data can be exposed before finally accepted by the collector.

D. Complexity

In this section, we analyze the communication and computational complexity of the proposed scheme. We use $N$ to denote the number of users and $T$ as the number of provider servers participated in a given data aggregation session. The number of communication rounds, the communication overheads, and the computation overheads will be compared with the prominent peer-shuffle protocol proposed in Dissent [6]. Dissent has implemented and evaluated only the “normal-cases” of the protocol, we also focus on the efficiency of our scheme assuming all checkings will be successfully passed.

1) Number of Communication Rounds: The server-user communications in phases 1, 4 (\(\Omega_{1,2}\) messages) and 6 (\(\Omega_{6,2}\) messages) are parallelizable and require 1 round. The communications between the collector server and the provider servers in phase 5 and phase 6 (\(\Omega_{6,1}\) messages) can be viewed as 1 round. The submission of EIMs in phase 2 is parallelizable and requires 1 round. Phase 3 cannot be parallelized and requires $N$ rounds. The exchange of hash values in phase 4 (\(\Omega_{4,1}\) messages) is parallelizable and requires 1 round. The total communication rounds for users is $N + 5$ (out of the overall communication rounds $N + 7$ for the whole IoT system). Dissent [6] considers the traditional one-server-multiple-users architecture, and has $N + 4$ communication rounds for users.

2) Communication Overheads: We use $X_0$ to denote the unified length for all plaintexts including data, index number, keys, etc. The serial regular public key encryption can keep the ciphertext in fixed-length, while the encryptions with padding will lead to a linear increase in ciphertext length. We use $X$ to denote the ciphertext length of regular encryptions, and $X'_{k}$ for the ciphertext length after $k$ rounds of encryptions with padding. The length of hash value and the signature are $H$ and $Y$, respectively. The total length of session ID and phase ID is denoted as $Z$. When aggregating data from $T$ providers, only a subset of phases need to be repeated in our scheme. Specifically, only message $\Omega_{1,2}$, $\Omega_5$, $\Omega_{6,1}$ and $\Omega_{6,2}$ are sent/received by the additional $(T - 1)$ providers. The per-user communication overhead of our scheme is $N^2(2X_0 + H + Y + Z) + N \cdot (\sum_{k=1}^{N} X'_k + (2T + 1)X'_1 + TX'_2 + X'_k + (2T + 3)Z + (2T + 3)Y)$. In contrast, the per-user communication overhead of Dissent [6] is $T \cdot N^2(2X_0 + H + 2Y + 2Z) + T \cdot N \cdot (\sum_{k=1}^{N} X'_k + 2Y + 2Z - H) - 2Y - 2Z$, which is approximately $T$ times as much as our scheme.

3) Computation Overheads: the $\text{Encpt}_R$, $\text{dect}_R$, $\text{Sign}$, $\text{Veri}$, $\text{Hash}$ and $\text{SH}$ are computations of encryption with padding, decryption of message encrypted with padding, signing function, verification of signature (also the session & phase ID), hashing function, and shuffle of $N$ objects, respectively. When $T$ providers are involved, the per-user computation overhead of our scheme is $(2N + 3T)\text{Encpt}_R + (2N + T + 1)\text{dect}_R + (T + 3)\text{Sign} + (N + 2T + 3)\text{Veri} + 2\text{Hash} + \text{SH} + O(N \log N)$. By comparison, the overhead of Dissent [6] is as large as $N T \text{Encpt}_R + N T \text{dect}_R + N T \text{Sign} + T(N + 3) \text{Veri} + 2T \text{Hash} + T \cdot \text{SH} + T \cdot O(N \log N)$, where $\text{Encpt}$ is the computation of regular public key encryption. Note that the complexity of these computations may vary with different length of inputs. Overall, Dissent has $O(T)$ times of computation overheads than our scheme. In the single-provider case, Dissent seems to have lighter per-user encryption overhead $O(N \cdot \text{Encpt} + N \cdot \text{dect}_R)$ compared to our scheme’s $O(2N \cdot \text{Encpt} + 2N \cdot \text{dect}_R)$. However, the output of $N$ rounds of $\text{Encpt}_R$ is the input of $N \cdot \text{Encpt}_R$ in Dissent, which means the computation of $N \cdot \text{Encpt}_R$ has
to wait until $N \cdot Encpt$ is done. In our scheme, the two sets of $N \cdot EncptR$ are for the collector data and index number, which can be computed in parallel.

VI. PERFORMANCE EVALUATIONS

We evaluate the performance of our anonymous data aggregation scheme through extensive simulations. All experiments were conducted on an Intel(R) Core(TM) i5 CPU 2.40GHz laptop with 4GB memory. The RSA/ECB/NoPadding and RSA/ECB/OAEPPWithSHA-1AndMGF1Padding cipher transformations in Java cryptography library are used for regular public key encryption and encryption with plaintext-expansion, respectively. In our testing program, each entity ran separately, and we counted the total execution time for a successful data aggregation. We also tested with different user group size, data size, and provider group size. The results presented are the average of 20 runs, and are compared with Dissent [6]. The public/private keys, signing/verification keys, and the secondary public/private keys (used in Dissent) are all 1024 bits. The links between two entities are 5 Mbps with a 100 ms node-to-node latency. Note that our implementation in Java slows down the execution of peer-shuffle compared to [6], but our main purpose is to demonstrate the relative advantage of our scheme over Dissent.

During implementation we found a practical issue: the plaintext is required to be smaller than the modulus for encryption algorithms like RSA. This can greatly impact the serial encryptions, since the ciphertext generated by a previous round of encryption may exceed the modulus in the next round. When it happens, the input has to be split for separate encryptions, which raises the computation workload and the length of the output ciphertext (i.e., extra cipher blocks). Dissent and our scheme both perform a set of serial encryptions with padding. Additionally, the data first go through another set of serial encryptions without padding in Dissent. If such issue occurs in an early stage, the resulted extra cipher blocks will get accumulated in each of the rest serial encryption rounds, triggering increasingly more overheads. Although it can be observed from the theoretical analysis that the two schemes have close overheads in single-provider case, the total execution time in Figures 5(a), 5(c) and the per-user communication overhead in Figures 5(b), 5(d) demonstrate that Dissent actually has greater overheads than our scheme.

Figures 5(a) and 5(b) present the total execution time and per-user communication overhead when different number of users are involved. The data length is 64 Byte. The execution time of both schemes increase with the user group size. Our scheme is more lightweight, especially when the group size is large. Since the serial encryptions/decryptions are the most time-consuming computations for both schemes and a larger user group size means more rounds of serial encryptions/decryptions, the efficiency advantage of our scheme is enlarged as the size of the user group increases. Similarly, the length of ciphertext data after serial encryptions will also increase with the user group size. Although different processors (users) have different communication overheads, the average value of per-user communication overheads grows larger with every round of encryption that is performed.

Figures 5(c) and 5(d) present the total execution time and per-user communication overhead with different data sizes. The user group size is 10. As we can see, the efficiency merit of our scheme in terms of computation and communication overheads shrinks as the data becomes longer. This is because the serial encryptions with padding hold the dominating part of the overheads when the data size is large, which covers the shortcomings of Dissent including the extra serial encryptions without padding and the aforementioned issue that leads to separate encryptions on plaintext.

Besides, our scheme supports the data aggregation from multiple providers, in which the peer-shuffle process including the serial encryptions/decryptions is conducted only once for the index messages. In contrast, the peer-shuffle processing is performed on both the collector data and each set of the provider data in Dissent, which produces huge computation
and communication overheads. Figures 5(e) and 5(f) present the performance of our scheme and Dissent when multiple providers are involved. The user group size is 10 and the data length is 64 Byte. While the total execution time and the per-user communication overheads of Dissent increase with the number of providers, it has little impact on our scheme.

VII. CONCLUSION

This paper studies the anonymous data aggregation across multiple companies in the IoT system. This problem cannot be solved properly by previous methods due to its special server-users-servers architecture. We proposed an efficient and accountable anonymous aggregation scheme, which utilizes the semi-trusted provider servers to improve efficiency, and provides resistance and accountability for various attacks. We analyzed and evaluated the communication and computation overheads of our scheme. The experimental results show that our scheme has great efficiency in data aggregation.

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