Edge-of-things computing framework for cost-effective provisioning of healthcare data

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HIGHLIGHTS

• Edge-of-Things (EoT) computation framework for healthcare service provisioning.
• Portfolio optimization approach for cost-effective healthcare data provisioning.
• Alternating direction method of multipliers (ADMM) for healthcare data offloading.

ABSTRACT

Edge-of-Things (EoT)-based healthcare services are forthcoming patient-care amenities related to autonomic and persuasive healthcare, where an EoT broker usually works as a middleman between the Healthcare Service Consumers (HSC) and Computing Service Providers (CSP). The computing service providers are the edge computing service providers (ECSP) and cloud computing service provider (CCSP). Sensor observations from a patient’s body area networks (BAN) and patients’ medical and genetic historical data are very sensitive and have a high degree of interdependency. It follows that EoT based patient monitoring systems or applications are tightly coupled and require obstinate synchronization. Therefore, this paper proposes a portfolio optimization solution for the selection of virtual machines (VMs) of edge and/or cloud computing service providers. The dynamic pricing for an EoT computation service is considered by the EoT broker for optimal VM provisioning in an EoT environment. The proposed portfolio optimization solution is compared with the traditional certainty equivalent approach. As the portfolio optimization is a centralized solution approach, this paper also proposes an alternating direction method of multipliers (ADMM) based distributed provisioning method for the healthcare data in the EoT computing environment. A comparative study shows the cost-effective provisioning for the healthcare data through portfolio optimization and ADMM methods over the traditional certainty equivalent and greedy approach, respectively.

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1. Introduction

Advancements in cloud computing [6], pervasive wireless broadband communication, body area networks, and wearable medical devices are empowering mobile healthcare services improving the welfare of both patients and health professionals [16]. Table 1 shows that the cost of healthcare is growing all over the world [21]. Finding ways to reduce healthcare costs is a major concern of governments, health insurances companies, hospitals, healthcare professionals, healthcare researchers, and patients. Several studies demonstrate that telehealth reduces the cost of healthcare [15]. Edge-of-Things (EoT)-based telehealth-care is a cost-effective solution for reducing per capita healthcare costs by utilizing EoT brokerage to ensure computation services from cloud service providers to healthcare service providers.

Consider the following telemedicine and e-healthcare scenario [2,4,12] where patients’ data are collected through wireless body area networks [23] and sensor observations are analyzed with respect to medical history, diagnostic results and genetic history in the cloud [5]. To analyze patient data, cloud service providers
charge for their per second CPU utilization time. The charges of various cloud service providers, which provide on-demand and multi-tenant computing as a service (CCaaS) [14], varies with respect to the requested VM instances, contract periods, location, time, and service availability [3]. For instance, windows azure demands $0.114 per hour for D2v2 instance of CPU usage and AWS charges at least $0.133 per hour for m3.large instance of CPU usage [18]. In this research work the EoT broker is the central entity for VM provisioning in Edge computing as a service (ECaaS) and Cloud computing as a service (CCaaS) providers in a cost-effective way, so that the broker can deliver smart-healthcare services to consumers with optimized cost.

2. Related works

The holistic approach, OPTIMIS, is proposed in [8] to optimize the service lifecycle of cloud service provisioning. That paper introduced a third-party broker for resource aggregation from a cloud infrastructure provider and offers those resources to consumer service providers. In the OPTIMIS, the service prices of different cloud infrastructure providers are not considered during service lifecycle optimization. The optimized placement of virtual machines in cloud brokering architecture is proposed in [22]. That paper presented a detailed architecture for a cloud service broker. The proper management of virtual resources of cloud brokers via a cloud scheduler was the most significant contribution of this research. However, the main drawback of this work is that authors did not consider dynamic cloud scheduling or dynamic pricing to use virtual machines for different services. A cloud broker’s infrastructure for e-healthcare services in a cloud environment is presented in [25]. The authors of this paper proposed a QoS-based optimization algorithm for a cloud broker to deliver requested healthcare services. The service charge of the cloud service provider is not considered in designing the objective function of the proposed optimization algorithm. The arrangement of processing clusters in a multi-cloud environment while considering the cost as most important parameter is described in [14]. The authors evaluated the system considering the point efficiency and cost. They utilized their work mostly for applications of the many-task computing (MTC). However, the proposed approach in [14] is not suitable for some applications related to tightly-coupled MTC. In tightly-coupled MTC applications, facts are basically interdependent. Further, the computational units in such systems demand a high level of synchronization, which is not plausible especially in decentralized EoT environment.

The optimal allocation of computing and networking resources in cloud computing networks is proposed in [17]. The authors of this paper used mixed-integer programming to formulate an optimal networked cloud mapping problem. In this paper, the authors did not consider a third-party cloud service broker for cloud service provisioning, thus they modeled the cloud request as an undirected graph of virtual nodes and virtual network links and then allocated physical resources according to the networked cloud requests. Energy-aware resource allocation and provisioning methods are discussed in [7]. They proposed a green cloud architecture with a power model, VMs placement, and migration algorithm. This proposal is on a power-aware policy development that minimizes the migration of VMs in a multi-cloud infrastructure. However, they did not consider cost-optimization in their proposal. Moreover, a genetic algorithm [9] based cost-effective service request scheduling technique is presented in [13] for SaaS providers. The model also maximizes the SaaS providers profit by maintaining SLA [18]. Additionally, the problem is formulated only for maximizing the revenue of SaaS provider, and the solution is not scalable to other cloud service providers [20]. The objective of their proposal is to balance the operational revenue and resource rental cost to earn more revenue.

To ensure optimal revenue of the cloud data center, coordinated VM resource preservation scheduling techniques were proposed in [26]. They formulated the resource maintenance issue of the data center as an Integer Linear Programming problem. Then, a transformation was made towards an equivalent problem with linear programming relaxation. Furthermore, the authors tried LIST rounding approach to approximate the solution of the problem.

Herein, the authors develop a schedule for physical servers maintenance to achieve less disruption of VMs by concentrating on cost- and recourse-aware placement of virtual machines in a multi-cloud environment. As far we know, the proposed cost-effective provisioning of healthcare data using an Edge-of-Things computing framework is pioneering research that leverages smart-healthcare via optimizing the data processing cost.

3. Edge-of-things (EoT) computing framework

The broker based edge-of-things (EoT) computing framework for smart-healthcare data provisioning is presented in Fig. 1. The framework entails three principal entities healthcare service consumers or enablers, EoT service broker, and EoT service providers. The healthcare service consumers are the end users of the patient-care system including patients and/or relatives, whereas healthcare service enablers are a doctor, nurse, hospital, clinic, imaging and diagnostic center, and rehabilitation center [1, 10, 11]. The EoT service providers are the infrastructure, platform and/or software application providers, which provide storage space, computation processors, network resources, and scalable software applications on demand via the internet, and charges with different rates for their services. In the proposed EoT computation framework (Fig. 1), we consider both edge and cloud computing service platforms as ECaaS (Edge Computing as a Service) and CCaaS (Cloud Computing as a Service), respectively. In EoT computing, both ECaaS
and CCaaS are necessary for cost-effective, reliable and smart-healthcare data processing. Finally, the EoT service brokers are the intermediary entity between healthcare service consumers and EoT computation service providers. The EoT service broker first receives an incoming service request from the healthcare service consumers. The broker explores the available virtual resources and their prices through virtual infrastructure manager (VIM). The VIM is also responsible for communication between EoT broker and computing service providers. Deployment of healthcare data to the VMs of ECaaS and CCaaS service provider is also managed by the VIM. Finally, the broker guarantees properly adjusted EoT services with the help of virtual infrastructure manager and scheduler.

The proposed resource optimization scheme is applied in the scheduler module of the EoT broker. The broker tries to select appropriate virtual machines (VMs) and EoT service providers. During the selection process, the broker considers the dynamic prices offered by the service providers. Further, it also checks the availability of the services that are provided by the EoT service providers. The aim of the dynamic selection process of the EoT service providers is mostly the optimization of healthcare costs for EoT-based healthcare services. For simplicity, only the computing service providers (CaaaS) provision has been considered for the healthcare service consumers and/or enablers.

In EoT framework, we assumed that the information and network security and data privacy are properly maintained by the entities of the framework through a standard cryptographic algorithm, communication protocols, and access control policy. The Elliptic Curve Cryptography (ECC) and Advanced Encryption Standard (AES) can be used for data and information security in hospital and cloud. The Secure Socket Layer (SSL), Internet Protocol Security (IPsec) and Wi-Fi Protected Access Protocol (WPA2) can be used in wired and wireless data communication between EoT service providers and healthcare service consumers or computing service providers. Moreover, the security and integrity of healthcare data can be assured through a decentralized block-chain technology. The EoT service consumers and EoT broker can form a block-chain network to preserve healthcare data integrity and security. Additionally, ECaaS providers and EoT broker can also form a block-chain network for healthcare data security. Furthermore, public key infrastructure-based security model can also be used for ensuring healthcare data security and preserving consumer’s privacy in the EoT framework [24].

4. Problem formulation

The optimized selection of ECaaS and CCaaS service providers can ensure cost-effective healthcare service provisioning in EoT based healthcare architecture through EoT brokers. Assume that, there are total $n$ VMs of $m$ ECaaS and CCaaS service providers. Each has different data processing capability and charges at a different rate for processing healthcare data based on their offered tariff. As the EoT broker receives a volume of requests from various healthcare service consumers, then for quicker delivery of the requested service, the EoT broker schedules and parallelizes the total data processing jobs to different VMs of the various computation service providers. Assume that the total submitted data volume from consumers is $v_{\text{totl}} \in \mathbb{R}^+$ for processing in $n$ VMs of $m$ computation service providers. Now, the problem is to distribute the volume of data $v_{\text{totl}}$ among the $n$ VMs of the $m$ service providers in a cost-effective manner, where VM $i$ of computation provider $s$ will process a volume of data $v_{ij}$. Each VM of any ECaaS or CCaaS provider can process a maximum volume of data $v_{max}$ and minimum volume of data $v_{min}$, because of its processing capability, and may also have the necessary bindings to securely process a given volume of healthcare data. The processing charge of each individual VM of ECaaS provider is different and denoted as $c_{ij}$ i.e. the cost of the VM $j$ of the ECaaS provider $s$. Therefore, $c_{ij}v$ is the total cost of processing the volume of healthcare data denoted as $v_{ij}$.

Due to unavailability, network failure or high traffic congestion of some of the VMs of an ECaaS provider may not be reachable or accessible in each and every time. The reachability factor is defined as a random variable $\mathbb{R}$, where the VMs of ECaaS provider $s$ is accessible at time $t$ with probability $r_{ij}$. The value of $r_{ij}$ lies between 0 and 1. As the VM of ECaaS provider has the processing capability of $v_{ij}$ volume of data and the probability $r_{ij}$ of receiving service from VM of ECaaS provider $s$, and also the service available from VM of provider $s$ is $v_{ij}r_{ij}$. Therefore, $v_{ij}r_{ij}$ represents the overall service obtainable at time $t$ from all possible available VMs. The EoT broker uses the software agent to find the available VMs. Considering the total service demand $v_{\text{totl}}$ of healthcare service consumers, the EoT broker first tries to provision the VMs of the ECaaS providers. However, if the requested service demand at time $t$ is higher than the available computing services of the ECaaS provider, i.e., $v_{\text{totl}} > v_{ij}r_{ij}$, then the EoT broker will provision the VMs from the CCaaS providers. The price of the CCaaS provider VMs is denoted as $p$. Hence, $E[p(v_{\text{totl}} - v_{ij}r_{ij})]$ denotes the expected cost of buying CCaaS provider services to fulfill the total service demand $v_{\text{totl}}$ of the healthcare service consumers. Now, the cost-effective VM provisioning for IoT healthcare data processing through edge and cloud computing becomes an optimization problem specifically minimizing the objective function (1).

$$c_{ij}v + E[p(v_{\text{totl}} - v_{ij}r_{ij})]$$

(1)

We can apply portfolio optimization methods to solve the above objective function of the optimization problem. The sample average approximation is one of the candidate approach for solving this portfolio selection problem because of the stochastic nature of the problem itself and since the objective function (1) has an expected value constraint. Thus, the solution of the optimization problem through the sample average approximation method can be formulated as (2), considering $(r_{ij}^{(k)}, r_{ij}^{(k)})$ as the set of samples through the joint distribution of total service request and availability of ECaaS VMs. Here, $k = 1, \ldots, N$ is the sample index and $N$ is the number of total samples.

$$c_{ij}v + \frac{1}{N} \sum_{k=1}^{N} p * (v_{\text{totl}}^{(k)} - v_{ij}r_{ij}^{(k)}).$$

(2)

Therefore, the sample average approximation (SAA) solution of the optimization problem (1) can be written as (3) through (6), where (3) is the redefined objective function and (4) to (6) are the constraints.

$$\text{minimize} \left( c_{ij}v + \frac{1}{N} \sum_{k=1}^{N} p * \max(0, (v_{\text{totl}}^{(k)} - v_{ij}r_{ij}^{(k)})) \right),$$

(3)

s.t. $v \geq v_{\text{min}}$  

(4)

$v \leq v_{\text{max}}$  

(5)

$v_{ij}r_{ij} \leq v_{\text{totl}}$  

(6)

The SAA solution may return near-optimal result because of the sample selection. Therefore, we used the validation set, which is denoted as $(\hat{v}_{\text{totl}}^{(k)}, \hat{r}_{ij}^{(k)})$, to test the validity of the optimal solution. Here $k = 1 \ldots N_{\text{val}}$, where $k$ is the sample index and $N_{\text{val}}$ is the number of total validation samples. Therefore, the formulation for validity checking optimization solution of the sample average approximation (SAV) can be written as follows, where (7) is the objective function and (8), (4) and (5) are the constraints.

$$\text{minimize} \left( c_{ij}v + \frac{1}{N_{\text{val}}} \sum_{k=1}^{N_{\text{val}}} p * \max(0, (\hat{v}_{\text{totl}}^{(k)} - v_{ij} \hat{r}_{ij}^{(k)})) \right),$$

(7)

s.t. $v_{ij} \hat{r}_{ij} \leq \hat{v}_{\text{totl}}$  

(8)
Fig. 2. VM provisioning in ECaaS and CCaaS providers using portfolio optimization approaches.

Table 2
Optimal costs of processing healthcare data in the EoT computation framework through portfolio optimization based VM provisioning.

| Optimization approaches | Chosen volume of healthcare data for processing | Optimal value | |
|-------------------------|-----------------------------------------------|---------------|
|                         | EP VM1 VM2 VM3 VM4 VM5 VM6 CP VM7            |               |
| (SAA)                   | 0.0 10.0 10.0 10.0 10.0 18.430 0.0 7.1960   | 0.0 7.1960    |
| (SAV)                   | 0.0 10.0 0.0 10.0 10.0 20.0 0.17750 7.3555 | 0.17750 7.3555|
| (CE-SAA)                | 0.0 10.0 10.0 10.0 10.0 18.430 0.0 7.1960   | 0.0 7.1960    |
| (CE-SAV)                | 0.0 10.0 0.0 10.0 10.0 20.0 0.17750 7.3555 | 0.17750 7.3555|

5. Performance study of portfolio optimization based healthcare data provisioning

The performance of the proposed healthcare data provisioning mechanism in an EoT computing environment is analyzed through a simulation study. To analyze the performance of the proposed portfolio-optimization-based solution approach, we compare it with the naive approach, i.e., the certainty-equivalent approach. The certainty-equivalent of the proposed sample average approximation (CE-SAA) solution can be derived using the optimization solution (9). The constraints of the CE-SAA problem are the same as the SAA problem.

\[
\text{minimize} \left( c^T v + p \cdot \max\left( 0, (\text{average}(v_{\text{total}}) - v^T \cdot \text{average}(r)) \right) \right) \quad (9)
\]

Similarly, the certainty-equivalent of the validity checking problem of the sample average approximation (CE-SAV) solution can be derived using the optimization solution (10). The constraints of the CE-SAV problem are the same as the SAV problem.

\[
\text{minimize} \left( c^T v + p \cdot \max\left( 0, (\text{average}(\hat{v}_{\text{total}}) - \hat{v}^T \cdot \text{average}(\hat{r})) \right) \right) \quad (10)
\]

To study the performance of the proposed healthcare data provisioning method, the CVX toolkit is used. In our performance study, we consider a total 7 VM instances. Out of the 7 VM instances, 6 are ECaaS providers (EP) and 1 is a CCaaS provider (CP) with a high configuration VM. The data processing charge of EP1 is considered as $0.14 per second, the CPU speed is 1 GHz, and it can process a maximum of 35 Gigabits of data for a single processing request from any EoT broker. The data processing charge of EP2 to EP5 is considered as $0.12 per second, the CPU speed of each of the processor is 1 GHz, and each of them can process a maximum 12 Gigabits of data for a single processing request from any EoT broker. The data processing charge of EP6 is considered as $0.13 per second, the CPU speed is 1 GHz, and it can process a maximum of 20 Gigabits of data for a single processing request from any EoT broker.

Finally, the data processing charge of the CCaaS service provider is considered as $0.20 per second and the CPU speed is 1 GHz, and it can process any demanded amount of data. The availability of the ECaaS provider is determined via the probability mass function (pmf) of the uniform distribution [0, 1]. The sample size of a submitted processing request from the broker to the ECaaS provider is 1,000 for the sample average approximation method, and 10,000 for the sample average validation. Table 2 shows the optimal cost of processing healthcare data, as determined via the proposed portfolio optimization method (SAA and SAV) and naive certainty-equivalent method (CE-SAA and CE-SAV) considering a processing request of 58.4311 GB data in an EoT environment. As SAA and certainty-equivalent SAA produced the same optimal results, then it follows that the proposed optimization formulation ensures optimal results. The different formulation of the optimization problem selects different ECaaS and CCaaS providers namely EP and CP, respectively. The proposed method also determines the processed data volume needed to provide a cost-effective solution for healthcare data processing in the EoT framework, as shown in Fig. 2. The comparative study between proposed SAA and SAV is performed considering the availability distribution of the ECaaS providers. The superiority performance of SAA with respect to the
cost-optimized VM provisioning for healthcare data processing in an EoT environment is shown in Fig. 3.

6. Distributed offloading solution through alternating direction method of multipliers (ADMM)

The portfolio optimization based solution is a centralized solution, which we studied in previous Section 5. The key benefit of the centralized solution approach is its capability of returning optimal result. However, the major drawback of centralized solution is its requirement of complete and whole information. Conversely, the Alternating Direction Method of Multipliers (ADMM) algorithm blended the decomposability of dual ascent with method of multipliers to facilitate decentralized optimality determination with superior convergence. In the proposed EoT framework, the EoT service broker receives large volume of data or requests from service consumers to offload computation at the network edge. For optimal provisioning of those healthcare data, we used ADMM optimization method, which can determine the optimal value through decentralized and parallel computation of optimal value with faster convergence. Furthermore, the ADMM based distributed solution approach can return optimal or near optimal results with minimal consensus messages. Therefore, the health-care data provisioning problem can be solved optimally in distributed Edge and Cloud nodes (i.e., ECAaS and CCAaaS providers), where EoT service broker acts as the message passing interface. For ADMM based solution, we redefined the problem, where \( x = (x_1, x_2, \ldots, x_M) \in \mathbb{R}^M \) is the set of available ECAaS and CCAaaS VMs. Therefore, the health-care data offloading (HDO) problem can be formulated as

\[
\text{HDO : } \min_x \quad z(x) \tag{11}
\]

s.t.

\[
\sum_{i=1}^M x_i = D \quad \tag{12}
\]

\[
x_i \leq \Pi_i, \quad \forall i \in M \quad \tag{13}
\]

\[
x_i \geq 0, \quad \forall i \in M \quad \tag{14}
\]

where \( z(x) = \sum_{i=1}^M \delta f_i(x_i) + (1 - \delta) t_i(x_i); \quad \Pi_i \) is the SLA parameters, and \( V_{\text{total}} = D \).

Therefore, we can write a set \( \mathcal{X} = \{ x : x \geq 0, \mathbf{1}^T x = D, x_i \leq \Pi_i \} \).

Then problem HDO can be written in ADMM as follows:

\[
\text{HDO : } \min_x \quad z(x) + g(y) \tag{15}
\]

s.t. \(
\quad x = y \quad \tag{16}
\)

Where \( y = (y_1, y_2, \ldots, y_M) \in \mathbb{R}^M \).

\[
g(y) = I_{\mathcal{X}}(y) = \begin{cases} 0, & y \in \mathcal{X} \\ \infty, & \text{otherwise} \end{cases} \tag{17}
\]

The augmented Lagrangian is as follows:

\[
\mathcal{L}_\nu(x, y, \nu) = z(x) + g(y) + \nu^T(y - z) + \frac{\rho}{2} \| y - x \|_2^2 \tag{18}
\]

Then the (unscale) ADMM update follows

\[
x^{(k+1)} = \arg \min_x \left[ z(x) - x^T \nu^{(k)} + \frac{\rho}{2} \| x - y^{(k)} \|_2^2 \right] \tag{19}
\]

\[
y^{(k+1)} = \arg \min_y \left[ g(y) + y^T \nu^{(k)} + \frac{\rho}{2} \| y - x^{(k+1)} \|_2^2 \right] \tag{20}
\]

\[
\nu^{(k+1)} = \nu^{(k)} + \rho(y^{(k+1)} - x^{(k+1)}) \tag{21}
\]

The \( y \)-update step solves the following problem:

\[
\min_y \quad y^T \nu^{(k)} + \frac{\rho}{2} \| y - x^{(k+1)} \|_2^2 \tag{22}
\]

s.t. \( \mathbf{1}^T y = D \tag{23} \)

\( y_i \leq \Pi_i \tag{24} \)

\( y \geq 0 \tag{25} \)

Using KKT condition, we can show that the solution of optimization is as follows:

\[
y_i^{(k+1)} = \left[ x_i^{(k+1)} - \frac{\mu + \nu_i^{(k)}}{\rho} \right]^+, \forall i \in M \tag{26}
\]

where \( [x]_+ = \max(x, 0) \), and \( \mu \in \mathbb{R} \) that satisfies following equation:

\[
\sum_{i=1}^M \left[ x_i^{(k+1)} - \frac{\mu + \nu_i^{(k)}}{\rho} \right]^+ = D \tag{27}
\]
The Julia 0.6.0 optimization package with Python programming is used to study the performance of ADMM based EoT framework. Fig. 4 shows the convergence of each variable of Eq. (19). The figure depicted that all of the variables are satisfied constraints and stable after isolation point within few iterations. For performance study, we also dynamically changed the prices of VMs of ECaaS and CCaaS providers. Fig. 5 shows that, in respect to data processing cost, ADMM based distributed method performs better provisioning of health-care data in EoT environment. However, portfolio optimization based centralized approach and ADMM based distributed approach returns the same results. Moreover, ADMM convergence to centralized solution results just after 67 iterations (as shown in Fig. 6).

7. Conclusion

The Edge-of-things (EoT) framework-based healthcare service provisioning enables personalized and smart-healthcare systems by leveraging healthcare data processing at the edge of the networks. The cost-effective patient-care system is the demand in need for sustainable smart-healthcare solutions. The proposed portfolio-optimization and ADMM-based approaches ensure cost-effective VM selection of ECaaS and CCaaS providers to analyzed data obtained from wearable sensors in e-health and m-health applications. Therefore, this approach will reduce the healthcare data processing costs by implementing the EoT framework. The introduced EoT broker is the key planner and optimizer in the proposed framework. The simplicity of the used portfolio optimization and the distributed nature of ADMM make these proposals effective for VM provisioning in the smart-healthcare system. However, the security and privacy of healthcare data are assumed to be assured through block chain or public key infrastructure-based security module both in the edge and cloud computing frameworks. The optimization methods of medical data storage costs, data security costs, and medical data transmission costs will be studied in the future extension of this research.

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