Leveraging Evolutionary Multiobjective Games for Configuring Cloud-integrated Body Sensor Networks

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Abstract—Body-in-the-Cloud (BitC) is a cloud-integrated architecture for body sensor networks (BSNs). This paper studies an evolutionary game theoretic algorithm to configure BSNs in an adaptive and stable manner. BitC allows BSNs to adapt their configurations (sensing intervals and sampling as well as data transmission intervals) to operational conditions (e.g., data request patterns) with respect to multiple performance objectives such as resource consumption and data yield. BitC theoretically guarantees that each BSN performs an evolutionarily stable configuration strategy, which is an equilibrium solution under given operational conditions. Simulation results verify this theoretical analysis; BSNs seek equilibria to perform adaptive and evolutionarily stable configuration strategies.

I. INTRODUCTION

Home healthcare is the most rapidly growing segment of the U.S. healthcare system since 1990s for both acute and chronic cares. In 2012, it recorded the highest spending growth (5.1%) among all healthcare segments in the US [1].

To address the quality of life and economic issues in home healthcare, various research efforts have been made for developing *body sensor networks* (BSNs), each of which is a per-patient wireless network of on/in-body sensors for, for example, heart rate, oxygen saturation, body temperature and fall detection [2]. BSNs can be used to remotely and continuously perform physiological and activity monitoring for homebound patients. This paper envisions *cloud-integrated* BSNs, which virtualize sensors with clouds for home healthcare by taking advantage of cloud computing features such as pay-per-use billing and scalability in data storage and processing.

This paper proposes an architecture for cloud-integrated BSNs, called Body-in-the-Cloud (BitC), which consists of the *sensor*, *edge* and *cloud* layers. The sensor layer is a collection of sensors and sensor nodes in BSNs. Each BSN operates sensor nodes, each of which is equipped with sensors and wirelessly connected to a dedicated per-patient device or a patient's computer (e.g., smartphone or tablet machine) that serves as a *sink* node. The edge layer consists of sink nodes, which collect sensor data from sensor nodes in BSNs. The cloud layer consists of cloud environments that host *virtual sensors*, which are virtualized counterparts (or software counterparts) of physical sensors in BSNs. Virtual sensors collect sensor data from sink nodes in the edge layer and store those data for future use. The cloud layer also hosts various applications that obtain sensor data from virtual sensors and aid medical staff (e.g., clinicians, hospital/visiting nurses and caregivers) to share sensor data for clinical observation and intervention.

BitC performs *push-pull hybrid communication* between its three layers. Each sensor node periodically collects data from sensors attached to it based on sensor-specific sensing intervals and sampling rates and transmits (or pushes) those collected data to a sink node. The sink node in turn forwards (or pushes) incoming sensor data periodically to virtual sensors in clouds. When a virtual sensor does not have sensor data that a cloud application requires, it obtains (or pulls) that data from a sink node or a sensor node. This push-pull communication is intended to make as much sensor data as possible available for cloud applications by taking advantage of push communication while allowing virtual sensors to pull any missing or extra data anytime in an on-demand manner. For example, when an anomaly is found in pushed sensor data, medical staff may pull extra data in a higher temporal resolution to better understand a patient's medical condition. Given a sufficient amount of data, they may perform clinical intervention, order clinical cares, dispatch ambulances or notify family members of patients.

This paper focuses on configuring BSNs in BitC by tuning sensing intervals and sampling rates for sensors as well as data transmission intervals for sensor and sink nodes, and studies two properties in configuring BSNs:

- *Adaptability*: Adjusting BSN configurations according to operational conditions (e.g., data request patterns placed by cloud applications and availability of resources such as bandwidth and memory) with respect to performance objectives such as bandwidth consumption, energy consumption and data yield.
- *Stability*: Minimizing oscillations (non-deterministic inconsistencies) in making adaptation decisions.

BitC leverages an evolutionary game theoretic approach to configure BSNs. Each BSN maintains a set (or a population) of configuration strategies. BitC theoretically guarantees that, through a series of evolutionary games between BSN configuration strategies, the population state (i.e., the distribution of strategies) converges to an evolutionarily stable equilibrium regardless of the initial state. (A dominant strategy in the evolutionarily stable population state is called an *evolutionarily stable strategy*.) In this state, no other strategies except an evolutionarily stable strategy can dominate the population. Given this theoretical property, BitC allows each BSN to

operate at equilibria by using an evolutionarily stable strategy to configure BSNs in a deterministic (i.e., stable) manner. Simulation results verify this theoretical analysis; BSNs seek equilibria to perform adaptive and evolutionarily stable configuration strategies. This paper also evaluates the performance of BitC with several parameter settings.
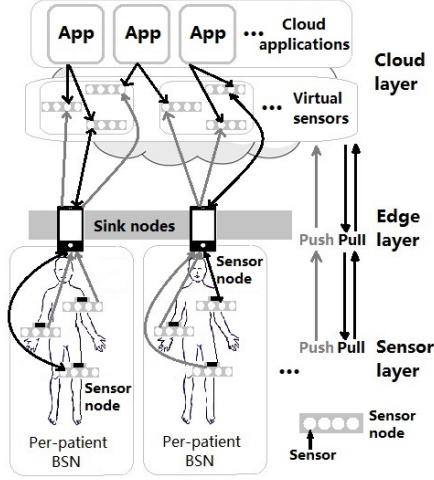

Fig. 1: A Push-Pull Hybrid Communication in BitC

II. An Architectural Overview of BitC

BitC consists of the following three layers (Fig. 1).

Sensor Layer: operates one or more BSNs on a per-patient basis (Fig. 1). Each BSN contains one or more sensor nodes in a certain topology. This paper assumes the star topology. Each sensor node is equipped with different types of sensors. It is assumed to be battery-operated. (It has limited energy supply.) It maintains a sensing interval and a sampling rate for each sensor attached to it. Upon a sensor reading, it stores collected data in its own memory space. Given a data transmission interval, it periodically flushes all data stored in its memory space and transmits the data to a sink node.

Edge Layer: consists of sink nodes, each of which participates in a certain BSN and receives sensor data periodically from sensor nodes in the BSN. A sink node stores incoming sensor data in its memory space and periodically flushes stored data to transmit (or push) them to the cloud layer. It maintains the mappings between physical and virtual sensors. In other words, it knows the origins and destinations of sensor data. Different sink nodes have different data transmission intervals. A sink node's data transmission interval can be different from the ones of sensor nodes in the same BSN. Sink nodes are assumed to have limited energy supplies through batteries.

In addition to pushing sensor data to a virtual sensor, each sink node receives a pull request from a virtual sensor when the virtual sensor does not have data that a cloud application(s) requires. If the sink node has the requested data in its memory, it returns that data. Otherwise, it issues another pull request to a sensor node that is responsible for the requested data. Upon receiving a pull request, the sensor node returns the requested data if it has the data in its memory. Otherwise, it returns an error message to a could application.

Cloud Layer: operates on clouds to host applications that allow medical staff to place continuous sensor data requests on virtual sensors in order to monitor patients. If a virtual

sensor has data that an application requests, it returns that data. Otherwise, it issues a pull request to a sink node. While push communication carries out a one-way upstream travel of sensor data, pull communication incurs a round trip for requesting sensor data and receiving that data (or an error message).

III. BSN Configuration Problem in BitC

This section describes a BSN configuration problem for which BitC seeks equilibrium solutions. Each BSN configuration consists of four types of parameters (i.e., decision variables): sensing intervals and sampling rates for sensors as well as data transmission intervals for sensor and sink nodes. The problem is stated with the following symbols.

- $B = \{b_1, b_2, ..., b_i, ..., b_N\}$ denotes the set of N BSNs, each of which operates for a patient.
- Each BSN b_i consists of a sink node (denoted by m_i) and M sensor nodes: $b_i = \{h_{i1}, h_{i2}, ..., h_{ij}, ..., h_{iM}\}$. Each sensor node h_{ij} has L sensors: $h_{ij} = \{s_{ij1}, s_{ij2}, ..., s_{ijk}, ..., s_{ijL}\}$. o_{ijk} is the data transmission interval for h_{ij} to transmit sensor data collected from s_{ijk}. p_{ijk} and q_{ijk} are the sensing interval and sampling rate for s_{ijk}. Sampling rate is defined as the number of sensor data samples collected in a unit time. Each sensor node stores collected sensor data in its memory space until its next push transmission. If the memory becomes full, it performs FIFO (First-In-First-Out) data replacement. In a push transmission, it flushes and sends out all data stored in its memory.
- o_{m_i} denotes the data transmission interval for m_i to forward (or push) sensor data incoming from sensor nodes in b_i In between two push transmissions, m_i stores sensor data from b_i in its memory. It performs FIFO data replacement if the memory becomes full. In a push transmission, it flushes and sends out all data stored in the memory.
- $R_{ijk} = \{r_{ijk1}, r_{ijk2}, ..., r_{ijkr}, ..., r_{ijk|R_{ijk}|}\}$ denotes the set of sensor data requests that cloud applications issue to the virtual counterpart of s_{ijk} (s'_{ijk}) during the time period of W in the past. Each request r_{ijkr} is characterized by its time stamp (t_{ijkr}) and time window (w_{ijkr}). It retrieves all sensor data available in the time interval $[t_{ijkr} - w_{ijkr}, t_{ijkr}]$. If s'_{ijk} has at least one data in the interval, it returns those data; otherwise, it issues a pull request to m_i.
- $R^m_{ijk} \subseteq R_{ijk}$ denotes the set of sensor data requests for which a virtual sensor s'_{ijk} has no data. $|R^m_{ijk}|$ indicates the number of pull requests that s'_{ijk} issues to m_i. In other words, $R_{ijk} \setminus R^m_{ijk}$ is the set of sensor data requests that s'_{ijk} fulfills regarding s_{ijk}.
- $R^s_{ijk} \subseteq R^m_{ijk} \subseteq R_{ijk}$ denotes the set of sensor data requests for which m_i has no data. $|R^s_{ijk}|$ indicates the number of pull requests that m_i issues to h_{ij} for collecting data from s_{ijk}. $R^m_{ijk} \setminus R^s_{ijk}$ is the set of sensor data requests that m_i fulfills regarding s_{ijk}.

This paper considers four performance objectives: bandwidth consumption between the edge and cloud layers (f_B), energy consumption of sensor and sink nodes (f_E), request fulfillment for cloud applications (f_R) and data yield for cloud applications (f_D). The first two objectives are to be minimized while the others are to be maximized.

The bandwidth consumption objective (f_B) is defined as the total amount of data transmitted per a unit time between the edge and cloud layers. This objective impacts the payment for bandwidth consumption based on a cloud operator's pay-per-use billing scheme. It also impacts the lifetime of sink nodes. f_B is computed as follows.

$$f_B = \frac{1}{W} \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L} (c_{ijk}d_{ijk}) + \frac{1}{W}\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L}\sum_{r=1}^{|R_{ijk}^m|} (\phi_{ijkr}d_{ijk} + d_r)$$
$$+ \frac{1}{W}\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L}\sum_{r=1}^{|R_{ijk}^s|} e_r(|R_{ijk}^s| - \eta_{ijkr}) \quad (1)$$

The first and second terms indicate the bandwidth consumption by one-way push communication from the edge layer to the cloud layer and two-way pull communication between the cloud and edge layers, respectively. c_{ijk} denotes the number of sensor data that s_{ijk} generates and sink nodes in turn push to the cloud layer during W. d_{ijk} denotes the size of each sensor data (in bits) that s_{ijk} generates. It is currently computed as: $q_{ijk} \times 16$ bits/sample. ϕ_{ijkr} denotes the number of sensor data that a pull request $r \in R_{ijk}^m$ can collect from sink nodes ($\phi_{ijkr} = |R_{ijk}^m \setminus R_{ijk}^s|$). d_r is the size of a pull request transmitted from the cloud layer to the edge layer. The third term in Eq. 1 indicates the bandwidth consumption by the error messages that sensors generate because they fail to fulfill pull requests. η_{ijkr} is the number of sensor data that a pull request $r \in R_{ijk}^s$ can collect from sensor nodes. e_r is the size of an error message.

The energy consumption objective (f_E) is defined as the total amount of energy that sensor and sink nodes consume for data transmissions during W. It impacts the lifetime of sensor and sink nodes. It is computed as follows.

$$f_E = \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L} \frac{W}{o_{ijk}} e_t d_{ijk} + \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L}\sum_{r=1}^{|R_{ijk}^s|} e_t \eta_{ijkr}(d_{ijk} + d_r')$$
$$+ \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L} \frac{W}{o_{m_i}} e_t d_{ijk} + \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L}\sum_{r=1}^{|R_{ijk}^m|} e_t \phi_{ijkr}(d_{ijk} + d_r)$$
$$+ 2 \times \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L}\sum_{r=1}^{|R_{ijk}^s|} e_t e_r(|R_{ijk}^s| - \eta_{ijkr}) \quad (2)$$

The first and second terms indicate the energy consumption by one-way push communication from the sensor layer to the edge layer and two-way pull communication between the edge layer and the sensor layer, respectively. e_t denotes the amount of energy (in Watts) that a sensor or sink node consumes to transmit a single bit of data. d_r' denotes the size of a pull request from the edge layer to the sensor layer. The third and fourth terms indicate the energy consumption by push and pull communication between the edge and cloud layer, respectively. The fifth term indicates the energy consumption for transmitting error messages on sensor and sink nodes.

The request fulfillment objective (f_R) is the ratio of the number of fulfilled requests over the total number of requests:

$$f_R = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L}\sum_{r=1}^{|R_{ijk}|} I_{R_{ijk}}}{|R_{ijk}|} \times 100 \quad (3)$$

$I_{R_{ijk}} = 1$ if a request $r \in R_{ijk}$ obtains at least one sensor data; otherwise, $I_{R_{ijk}} = 0$.

The data yield objective (f_Y) is defined as the total amount of data that cloud applications gather for their users. This objective impacts the informedness and situation awareness for application users. It is computed as follows.

$$f_Y = \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L}\sum_{r=1}^{|R_{ijk}^m|} \phi_{ijkr} + \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{L}\sum_{r=1}^{|R_{ijk}^s|} \eta_{ijkr} + c_{ijk} \quad (4)$$

BitC considers four constraints. The first constraint (C_E) is the upper limit for energy consumption: $f_E < C_E$. A violation for the constraint (g_E) is computed as $g_E = I_E \times (f_E - C_E)$ where $I_E = 1$ if $f_E > C_E$; otherwise $I_E = 0$.

The second constraint (C_Y) is the lower limit for data yield: $f_Y > C_Y$. A constraint violation (g_Y) is computed as $g_Y = I_Y \times (C_Y - f_Y)$ where $I_Y = 1$ if $f_Y < C_Y$; otherwise $I_Y = 0$.

The third constraint (C_R) is the lower limit for request fulfillment: $f_R > C_R$. The constraint violation in request fulfillment (g_R) is computed as $g_R = I_R \times (C_R - f_R)$ where $I_R = 1$ if $f_R < C_R$; otherwise $I_R = 0$.

The fourth constraint (C_B) is the upper limit for bandwidth consumption: $f_B < C_B$. A violation for this constraint (g_B) is computed as $g_B = I_B \times (f_B - C_B)$ where $I_B = 1$ if $f_B > C_B$; otherwise $I_B = 0$.

IV. BACKGROUND: EVOLUTIONARY GAME THEORY

In a conventional game, the objective of a player is to choose a strategy that maximizes its payoff in a single game. In contrast, evolutionary games are played repeatedly by players randomly drawn from a population [3]. This section overviews key elements in evolutionary games: evolutionarily stable strategies (ESS) and replicator dynamics.

A. Evolutionarily Stable Strategies (ESS)

Suppose all players in the initial population are programmed to play a certain (incumbent) strategy k. Then, let a small population share of players, $x \in (0, 1)$, mutate and play a different (mutant) strategy ℓ. When a player is drawn for a game, the probabilities that its opponent plays k and ℓ are $1 - x$ and x, respectively. Thus, the expected payoffs for the player to play k and ℓ are denoted as $U(k, x\ell + (1-x)k)$ and $U(\ell, x\ell + (1-x)k)$, respectively.

Definition 1. *A strategy k is said to be evolutionarily stable if, for every strategy $\ell \neq k$, a certain $\bar{x} \in (0, 1)$ exists, such that the inequality*

$$U(k, \; x\ell + (1-x)k) > U(\ell, \; x\ell + (1-x)k) \quad (5)$$

holds for all $x \in (0, \bar{x})$.

If the payoff function is linear, Equation 5 derives:

$$(1-x)U(k,k) + xU(k,\ell) > (1-x)U(\ell,k) + xU(\ell,\ell) \quad (6)$$

If x is close to zero, Equation 6 derives either

$$U(k,k) > U(\ell,k) \; or \; U(k,k) = U(\ell,k) \; and \; U(k,\ell) > U(\ell,\ell) \quad (7)$$

This indicates that a player associated with the strategy k gains a higher payoff than the ones associated with the other strategies. Therefore, no players can benefit by changing their strategies from k to the others. This means that an ESS is a solution on a Nash equilibrium. An ESS is a strategy that cannot be invaded by any alternative (mutant) strategies that have lower population shares.

B. Replicator Dynamics

The replicator dynamics describes how population shares associated with different strategies evolve over time [4]. Let $\lambda_k(t) \geq 0$ be the number of players who play the strategy $k \in K$, where K is the set of available strategies. The total population of players is given by $\lambda(t) = \sum_{k=1}^{|K|} \lambda_k(t)$. Let $x_k(t) = \lambda_k(t)/\lambda(t)$ be the population share of players who play k at time t. The population state is defined by $X(t) = [x_1(t), \cdots, x_k(t), \cdots, x_K(t)]$. Given X, the expected payoff of playing k is denoted by $U(k, X)$. The population's average payoff, which is same as the payoff of a player drawn randomly from the population, is denoted by $U(X, X) = \sum_{k=1}^{|K|} x_k \cdot U(k, X)$. In the replicator dynamics, the dynamics of the population share x_k is described as follows. $\dot{x}_k$ is the time derivative of x_k.

$$\dot{x}_k = x_k \cdot [U(k, X) - U(X, X)] \qquad (8)$$

This equation states that players increase (or decrease) their population shares when their payoffs are higher (or lower) than the population's average payoff.

Theorem 1. *If a strategy k is strictly dominated, then* $x_k(t)_{t \to \infty} \to 0$.

A strategy is said to be strictly dominant if its payoff is strictly higher than any opponents. As its population share grows, it dominates the population over time. Conversely, a strategy is said to be strictly dominated if its payoff is lower than that of a strictly dominant strategy. Thus, strictly dominated strategies disappear in the population over time.

There is a close connection between Nash equilibria and the steady states in the replicator dynamics, in which the population shares do not change over time. Since no players change their strategies on Nash equilibria, every Nash equilibrium is a steady state in the replicator dynamics. As described in Section IV-A, an ESS is a solution on a Nash equilibrium. Thus, an ESS is a solution at a steady state in the replicator dynamics. In other words, an ESS is the strictly dominant strategy in the population on a steady state.

BitC maintains a population of configuration strategies for each BSN. In each population, strategies are randomly drawn to play games repeatedly until the population state reaches a steady state. Then, BitC identifies a strictly dominant strategy in the population and configures a BSN based on the strategy as an ESS.

V. Body-in-the-Cloud

BitC maintains N populations, $\{\mathcal{P}_1, \mathcal{P}_2, ..., \mathcal{P}_N\}$, for N BSNs and performs games among strategies in each population. Each strategy $s(b_i)$ specifies a particular configuration for a BSN b_i using four types of parameters: sensing intervals and sampling rates for sensors (p_{ijk} and q_{ijk}) as well as data transmission intervals for sink and sensor nodes (o_{m_i} and o_{ijk}).

$$s(b_i) = \bigcup_{j \in \{1..M\}} \bigcup_{k \in \{1..L\}} (o_{m_i}, o_{ijk}, p_{ijk}, q_{ijk}) \; 1 < i < N \qquad (9)$$

Algorithm 1 shows how BitC seeks an evolutionarily stable configuration strategy for each BSN through evolutionary games. In the 0-th generation, strategies are randomly generated for each of N populations $\{\mathcal{P}_1, \mathcal{P}_2, ..., \mathcal{P}_N\}$ (Line 2). Those strategies may or may not be feasible. Note that a strategy is said to be feasible if it violates none of four constraints described in Section III.

In each generation (g), a series of games are carried out on every population (Lines 4 to 26). A single game randomly chooses a pair of strategies (s_1 and s_2) and distinguishes them to the winner and the loser with respect to performance objectives described in Section III (Lines 7 to 9). The loser disappears in the population. The winner is replicated to increase its population share and mutated with polynomial mutation (Lines 10 to 17) [5]. Mutation randomly chooses a parameter (or parameters) in a given strategy with a certain mutation rate P_m and alters its/their value(s) at random (Lines 12 to 14).

Once all strategies play games in the population, BitC identifies a feasible strategy whose population share (x_s) is the highest and determines it as a dominant strategy (d_i) (Lines 20 to 24). BitC configures a BSN with parameters contained in the dominant strategy.

Algorithm 1 Evolutionary Process in BitC

1: $g = 0$
2: Randomly generate the initial N populations for N BSNs: $\mathcal{P} = \{\mathcal{P}_1, \mathcal{P}_2, ..., \mathcal{P}_N\}$
3: **while** $g < G_{max}$ **do**
4:   **for each** population $\mathcal{P}_i$ randomly selected from $\mathcal{P}$ **do**
5:     $\mathcal{P}'_i \leftarrow \emptyset$
6:     **for** $j = 1$ to $|\mathcal{P}_i|/2$ **do**
7:       $s_1 \leftarrow$ randomlySelect($\mathcal{P}_i$)
8:       $s_2 \leftarrow$ randomlySelect($\mathcal{P}_i$)
9:       $winner \leftarrow$ performGame(s_1, s_2)
10:      $replica \leftarrow$ replicate($winner$)
11:      **for each** parameter in $replica$ **do**
12:        **if** random() $\leq P_m$ **then**
13:         $replica \leftarrow$ mutate($winner$)
14:        **end if**
15:      **end for**
16:      $\mathcal{P}'_i \leftarrow \mathcal{P}_i \setminus \{s_1, s_2\}$
17:      $\mathcal{P}'_i \leftarrow \mathcal{P}'_i \cup \{winner, replica\}$
18:     **end for**
19:     $\mathcal{P}_i \leftarrow \mathcal{P}'_i$
20:     $d_i \leftarrow argmax_{s \in \mathcal{P}_i} x_s$
21:     **while** d_i is infeasible **do**
22:       $\mathcal{P}_i \leftarrow \mathcal{P}_i \setminus \{d_i\}$
23:       $d_i \leftarrow argmax_{s \in \mathcal{P}_i} x_s$
24:     **end while**
25:     Configure a BSN in question based on d_i.
26:   **end for**
27:   $g = g + 1$
28: **end while**

Algorithm 2 shows how to select the winner in a game (`performGame()` in Algorithm 1). This selection process depends on the dominance relationship between given two strategies and their feasibility. A feasible strategy s_1 is said to dominate another feasible strategy s_2 (denoted by $s_1 \succ s_2$) if both of the following conditions are hold:

- s_1's objective values are superior than, or equal to, s_2's in all objectives.
- s_1's objective values are superior than s_2's in at least one objectives.

If given two strategies are feasible and they are non-dominated with each other, the winner is randomly chosen (Line 8). If both of them are infeasible, their dominance relationship is determined based on their constraint violation (Lines 17 to 23). An infeasible strategy s_1 is said to dominate another infeasible strategy s_2 ($s_1 \succ_C s_2$) iif:

- s_1's constraint violation is lower than, or equal to, s_2's in every constraint, and
- s_1's constraint violation is lower than s_2's in at least one constraints.

Algorithm 2 Game between Strategies (`performGame()`)

Input: s_1 and s_2: Strategies to play a game
Output: Winner of the game
1: **if** s_1 and s_2 are feasible **then**
2:    **if** $s_1 \succ s_2$ **then**
3:       **return** s_1
4:    **end if**
5:    **if** $s_2 \succ s_1$ **then**
6:       **return** s_2
7:    **end if**
8:    **return** randomlySelect($\{s_1, s_2\}$)
9: **end if**
10: **if** s_1 is feasible and s_2 is infeasible **then**
11:    **return** s_1
12: **end if**
13: **if** s_2 is feasible and s_1 is infeasible **then**
14:    **return** s_2
15: **end if**
16: **if** s_1 and s_2 are infeasible **then**
17:    **if** $s_1 \succ_C s_2$ **then**
18:       **return** s_1
19:    **end if**
20:    **if** $s_2 \succ_C s_1$ **then**
21:       **return** s_2
22:    **end if**
23:    **return** randomlySelect($\{s_1, s_2\}$)
24: **end if**

VI. STABILITY ANALYSIS

This section analyzes BitC's stability (i.e., reachability to at least one of Nash equilibrium) by proving the state of each population converges to an evolutionarily stable equillibrium. The proof consists of three steps: (1) designing a set of differential equations that describe the dynamics of the population state, (2) proving an strategy selection process has equilibria, and (3) proving the the equilibria are asymptotically (or evolutionarily) stable. The proof uses the following symbols:

- S denotes the set of available strategies. S^* denotes a set of strategies that appear in the population.
- $X(t) = \{x_1(t), x_2(t), \cdots, x_{|S^*|}(t)\}$ denotes a population state at time t where $x_s(t)$ is the population share of a strategy $s \in S$. $\sum_{s \in S^*}(x_s) = 1$.
- F_s denotes the fitness of a strategy s. It is a relative value that is determined in a game against an opponent based on the dominance relationship between them (Algorithm 2). The winner of a game earns a higher fitness than the loser.
- $p_k^s = x_k \cdot \phi(F_s - F_k)$ denotes the probability that a strategy s is replicated by winning a game against another strategy k. $\phi(F_s - F_k)$ is the probability that the fitness of s is higher than that of k.

The dynamics of the population share of s is described as:

$$
\begin{aligned}
\dot{x}_s &= \sum_{k \in S^*, k \neq s} \{x_s p_k^s - x_k p_s^k\} \\
&= x_s \sum_{k \in S^*, k \neq s} x_k \{\phi(F_s - F_k) - \phi(F_k - F_s)\} \quad (10)
\end{aligned}
$$

Note that if s is strictly dominated, $x_s(t)_{t \to \infty} \to 0$.

Theorem 2. *The state of a population converges to an equilibrium.*

   Proof: It is true that different strategies have different fitness values. In other words, only one strategy has the highest fitness among others. Given Theorem 1, assuming that $F_1 > F_2 > \cdots > F_{|S^*|}$, the population state converges to an

equilibrium: $X(t)_{t \to \infty} = \{x_1(t), x_2(t), \cdots, x_{|S^*|}(t)\}_{t \to \infty}$ $= \{1, 0, \cdots, 0\}$. ∎

Theorem 3. *The equilibrium found in Theorem 2 is asymptotically stable.*

   Proof: At the equilibrium $X = \{1, 0, \cdots, 0\}$, a set of differential equations can be downsized by substituting $x_1 = 1 - x_2 - \cdots - x_{|S^*|}$

$$
\dot{z}_s = z_s[c_{s1}(1 - z_s) + \sum_{i=2, i \neq s}^{|s^*|} z_i \cdot c_{si}], \quad s, k = 2, ..., |S^*| \quad (11)
$$

where $c_{sk} \equiv \phi(F_s - F_k) - \phi(F_k - F_s)$ and $Z(t) = \{z_2(t), z_3(t), \cdots, z_{|S^*|}(t)\}$ denotes the corresponding downsized population state. Given Theorem 1, $Z_{t \to \infty} = Z_{eq} = \{0, 0, \cdots, 0\}$ of $(|S^*| - 1)$-dimension.

If all Eigenvalues of Jaccobian matrix of $Z(t)$ has negative real parts, Z_{eq} is asymptotically stable. The Jaccobian matrix J's elements are described as follows where $s, k = 2, ..., |S^*|$.

$$
J_{sk} = \left[\frac{\partial \dot{z}_s}{\partial z_k}\right]_{|Z=Z_{eq}} = \left[\frac{\partial z_s[c_{s1}(1 - z_s) + \sum_{i=2, i \neq s}^{|S^*|} z_i \cdot c_{si}]}{\partial z_k}\right]_{|Z=Z_{eq}} \quad (12)
$$

Therefore, J is given as follows, where $c_{21}, c_{31}, \cdots, c_{|S^*|1}$ are J's Eigenvalues.

$$
J = \begin{bmatrix}
c_{21} & 0 & \cdots & 0 \\
0 & c_{31} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & c_{|S^*|1}
\end{bmatrix} \quad (13)
$$

$c_{s1} = -\phi(F_1 - F_s) < 0$ for all s; therefore, $Z_{eq} = \{0, 0, \cdots, 0\}$ is asymptotically stable. ∎

VII. SIMULATION EVALUATION

This section evaluates BitC through simulations and discusses how BitC allows BSNs to to adapt their configurations to given operational conditions (e.g., data request patterns placed by cloud applications and memory space availability in sink and sensor nodes) Simulations are configured with the parameters shown in Table I.

TABLE I: Simulation Settings

Parameter	Value
Duration of a simulation (W)	10,800 seconds (3 hours)
Number of BSNs (N)	10
Number of sensor nodes in a BSN (M)	3
Number of sensors per a sensor node (L)	4
Memory space in a sensor node	2 GB
Memory space in a sink node	16 GB
Total number of data requests from cloud apps	1,000
Size of a data request (d_r and d_r')	100 bytes
Size of an error message (e_r)	250 bytes
Energy consumption for a single bit of data (e_t)	0.001 Joules
Time window for a data request to a body temp sensor	[0, 60 secs]
Time window for a data request to an oximeter	[0, 60 secs]
Time window for a data request to an acelerometer	[0, 1800 secs]
Time window for a data request to an ECG sensor	[0, 600 secs]
Number of generations (G_{max})	400
Population size ($|\mathcal{P}_i|$)	100
Mutation rate (P_m)	$1/v$
Upper limit of bandwidth consumption (C_B)	100 Kbps
Lower limit of data yield (C_Y)	6000
Upper limit of energy consumption (C_E)	1 Watt
Lower limit of request fulfillment (C_R)	95%

Cloud applications issue 1,000 data requests during three hours. Requests are uniformly distributed over virtual sensors.
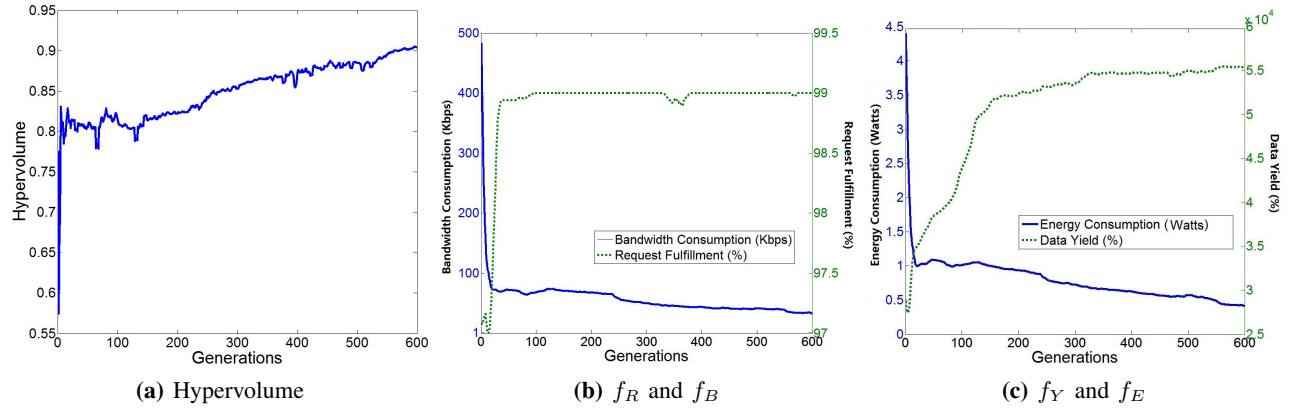
Fig. 2: Hypervolume and Objective Values (Request Fulfillment: f_R, Bandwidth Consumption: f_B, Data Yield: f_Y, Energy Consumption: f_E)

Each sensor node contains four sensors: body temperature sensor, oximeter, accelerometer and ECG sensor. A time window is randomly set for each request to a sensor. For example, it is set with the uniform distribution in between 0 and 60 seconds for an oximeter. Mutation rate is set to $1/v$ where v is the number of parameters in a strategy. Every simulation result is the average with 20 independent simulation runs.

Table II examines how a mutation-related parameter, called distribution index (η_m in [5]), impacts the performance of BitC. This parameter controls how likely a mutated strategy is similar to its original. (A higher distribution index makes a mutant more similar to its original.) In Table II, the performance of BitC is evaluated with the hypervolume measure that a set of dominant strategies yield in the 400th generation. The hypervolume metric indicates the union of the volumes that a given set of solutions dominates in the objective space [6]. A higher hypervolume means that a set of solutions is more optimal. As shown in Table II, BitC yields the best performance with the distribution index value of 45. (No constraints are set to obtain this result.) Thus, this parameter setting is used in all successive simulations.

TABLE II: Impacts of Distribution Index Values on Hypervolume

Distribution Index	Hypervolume	Distribution Index	Hypervolume
10	0.848	45	0.878
20	0.861	50	0.855
30	0.871	60	0.797
40	0.874		

Fig. 2 shows how BitC improves its performance through generations. Four constraints (C_B, C_Y, C_E and C_R) are enabled. (Table I). Fig. 2a shows how hypervolume increases through generations. At each generation, hypervolume is measured with a set of dominant strategies taken from individual populations. Hypervolume increases rapidly in the beginning of a simulation and exceeds 0.8 around the 30th generation. It reaches 0.9 at the last generation. Figs. 2b and 2c show the changes of objective values over generations. All four constraints are satisfied at the last generation. The two figures illustrate that BitC improves its objective values subject to given constraints by balancing the trade-offs among conflicting objectives. For example, in Fig. 2b, BitC improves both request fulfillment and bandwidth consumption through generations while the two objectives conflict with each other.

Fig. 3 shows two three-dimensional objective spaces that

plot a set of dominant strategies obtained from individual populations at each generation. Each blue dot indicates the average objective values that dominant strategies yield at a particular generation in 20 simulation runs. The trajectory of blue dots illustrates a path through which strategies evolve and improve objective values. Gray and red dots represent 20 different sets of objective values at the first and last generation in 20 simulation runs, respectively. While initial (gray) dots disperse (because strategies are generated at random initially), final (red) dots are clustered in a smaller region(s). This implies BitC's stability: reachability to at least one Nash equilibria regardless of the initial conditions.
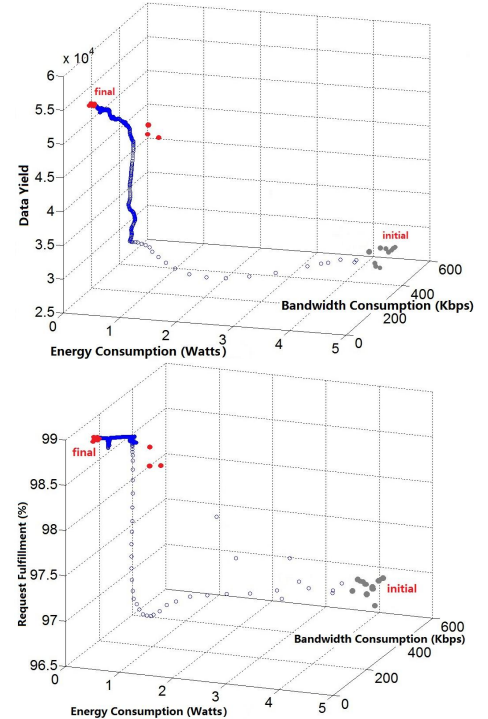

Fig. 3: Three-dimensional Objective Spaces

Table III and Figure 4 show how different constraint combinations impact on the performance of BitC in objective values and hypervolume, respectively. BitC successfully satisfies all the constraint combinations by generating different shapes/amounts of hypervolume. In general, it generates lower hypervolume when stricter constraints are given.

TABLE III: Objective Values at the Last Generation under Different Sets of Constraints

| Constraint Combination		Request Fulfillment (%)	Bandwidth Consumption (Kbps)	Data Yield	Energy Consumption (Watts)
C_B: 300 C_Y: 20,000 C_R: 90 C_E: 3.0	Max	98.2	45.01	66,225	0.68
	Avg	98	42.68	62,500	0.62
	Min	97.9	39.33	57,530	0.57
C_B: 50 C_E: 10	Max	97.1	28.03	41,666	0.41
	Avg	97	26.88	40,816	0.39
	Min	97	25.62	39,884	0.37
C_Y: 50000 C_R: 95	Max	98.3	164.58	64,935	1.59
	Avg	97.6	148.49	62,227	1.43
	Min	97	123.86	58,898	1.22
C_Y: 50000 C_R: 98	Max	99	58.21	65,789	0.65
	Avg	98.7	53.32	64,102	0.625
	Min	98.5	49.02	63,388	0.58
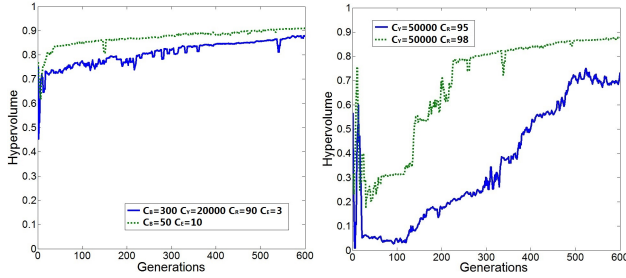
Fig. 4: Hypervolume under Different Sets of Constraints

VIII. Related Work

This paper extends a prior work on cloud-integrated BSNs [7]. Compared to [7], this paper formulates a more realistic problem by accommodating parameters configurable in Simmer's sensor nodes[1]. Moreover, this paper uses an evolutionary game theoretic algorithm that possesses stability in configuring BSNs while a genetic algorithm is used in [7]. As stochastic search algorithms, genetic algorithms lack stability.

Various architectures and research tools have been proposed for cloud-integrated sensor networks including BSNs [8]–[13]. Hassan et al. [8], Aberer et al. [9], Gaynor et al. [10] and Boonma et al. [11] assume three-tier architectures similar to BitC and investigate publish/subscribe communication between the edge layer to the cloud layer. Their focus is placed on push communication. In contrast, BitC investigates push-pull hybrid communication between the sensor layer and the cloud layer through the edge layer. Yuriyama et al. propose a two-tier architecture that consists of the sensor and cloud layers [12]. The architectures proposed by Yuriyama et al. and Fortino et al. [13] are similar to BitC in that they leverage the notion of virtual sensors. However, they do not consider push-pull (nor publish/subscribe) communication. All the above-mentioned work do not consider adaptive/stable configurations of sensor networks as BitC does.

Push-pull hybrid communication has been studied in sensor networks [14]–[17]. However, few efforts exist to study it between the edge and cloud layers in the context of cloud-integrated sensor networks. Unlike those relevant work, this paper formulates a sensor network configuration problem with cloud-specific objectives as well as the ones in sensor networks and seeks adaptive/stable solutions for the problem.

IX. Conclusion

This paper considers a layered push-pull hybrid communication for cloud-integrated BSNs and formulates a BSN configuration problem to seek equilibrium solutions. An evolutionary game theoretic algorithm is used to approach the problem. A theoretical analysis proves that the proposed algorithm allows each BSN to operate at an equilibrium by using an evolutionarily stable configuration strategy in a deterministic (i.e., stable) manner. Simulation results verify this theoretical analysis; BSNs seek equilibria to perform adaptive and evolutionarily stable configuration strategies.

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