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In-Network Computations of Machine-to-Machine Communications for Wireless Robotics

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Abstract Wireless robotics enables wide applications of service robots to benefit human life. However, effective machine-to-machine communications would be the foundation of operation. With cloud-based architecture, we innovatively demonstrate in-network computation to significantly alleviate the requirement of communication bandwidth for multi-hop networking, to achieve spectrum-efficient M2M communications. We further characterize the coverage geographical of machines to impact effective operation of wireless robotics.

Keywords In-network computation · Data reduction · Information collection · Networked robotics · Wireless robotics · Machine-to-machine communications · Sensor networks · Ad hoc networks

1 Introduction

Migrating from manufacturing robotics and later entertainment robotics, service robotics attracts tremendous research interests as a new frontier of information communication technology (ICT). Autonomous wireless communications among machines, known as machine-to-machine (M2M) communications, play the critical role to control these intelligent machines and to execute intelligent missions. We name robotics of M2M communications capability as wireless robotics. Typical communication capability for service robots aims at

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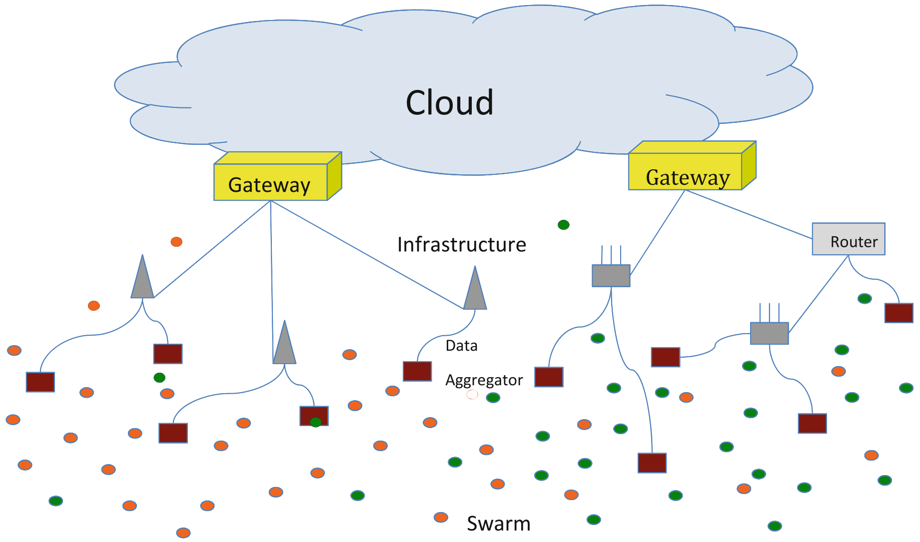

Fig. 1 Cloud-based M2M communications

special purpose such as rescue robotics [1], or control and commend within a robot squad [2] with potential multi-hop ad hoc networking [3]. Under the scenario of cloud computing, M2M communications and subsequent wireless robotics based on cloud open a new era in wireless communications [4,5], to enable close interaction of cyber-physical systems [6].

We summarize the M2M communication architecture as Fig. 1 Cloud connects data centers and servers, to enable and to maintain variety of services. Through gateways to wireless infrastructure that supports high bandwidth for transparent communication and networking in operations. Wireless infrastructure shall be 3GPP type cellular systems [7], or IEEE 802 type wide/local area networks. Wireless infrastructure typically connects data aggregators (DAs) that collect or exchange information with small traffic-load machines (such as sensors), such that sensors can only equip simple wireless communication capability via appropriate battery efficient short-range wireless communication methodology. Such sensors or machines can be viewed as machine swarm/ocean due to tremendous number of wireless devices, typically several orders more than todays wireless personal communication systems like cellular networks. The deployment of machine swarm cannot be fully controlled, while only DAs might be possibly controlled. Therefore, a heterogeneous network structure is formed [8], and is widely investigated in recent literature. To ensure quality-of-service under such cyber-physical system scenario, a systematic approach, even under spectrum sharing, has been successfully developed [9].

Machine swarm communications face a few technical challenges:

1. Spectrum Scarcity: Limited spectrum is likely available for such a huge number of wireless devices. Though each device might have limited traffic volume and low duty cycle, the aggregated traffic with considered overhead in classic multiple access [10] creates a new challenge for energy-efficient access. Consequently, spectrum sharing is expected. Spectrum sharing can be realized in two ways: wireless devices in multiple systems/networks to share a common frequency band like todays 2.4 GHz ISM band (except much more busy spectrum utilization and likely less control), or cognitive radio [11,12] allowing machines to transport their traffic in certain moments when the primary system does not

utilize the spectrum. Spectrum efficiency shall be counted on end-to-end throughput per bandwidth, rather than bits per bandwidth in physical layer transmission.
2. Scalability: M2M communications have to deal with different scales of information exchange, and thus scalability is critical in real applications.
3. Deployment and Device Management: Successful M2M communications rely on effective deployment of machines/sensors. Most of machines/sensors have limited reliability due to practical concerns. Under defection of out of battery, device management [13] determines whether M2M communications can serve the system in a long run.

Furthermore, above study usually assumes low-mobility, while vehicular M2M communications under such scenario is rather open at this time, such as wireless robotics. Consequently, a new challenge for M2M communications in wireless robotics is mobility. In this paper, we are going to explore mobility and other challenges associated with mobility, and thus to propose a new angle to design information system supporting wireless robotics. Past design philosophy to transport data to destination for processing and/or computing might not be efficient anymore. Tradeoff between communications and in-network computations inside the system shall be the way enabling wireless robotics as we can see from this paper.

This paper is organized as follows. Cloud-based M2M communication architecture and related technology considerations are described in Sect. 2. We introduce in-network computation to exchange communication bandwidth via a novel compress-and-forward routing for multi-hop networking, in Sect. 3. Further system operation issues are discussed in Sect. 4.

2 Cloud-Based M2M Communication Architecture for Wireless Robotics and Enabling Technology

Robotics via Internet has been investigated for years [14], which is further fertilized by cloud computing [1]. With mobile communication into the focus of picture, the network architecture for wireless robotics can be specifically suggested and illustrated as the heterogeneous network structure in Fig. 2. The solid black lines or curves stand for wired or wireless backbone networking to the cloud. The control center monitors the activities of robots, through the data aggregator (DA) that collects or exchanges information with sensors on each robot. In the field or on the roadside, there are tremendous machines (including DAs) or sensors to form the machine swarm, which can collect varieties of information for the operation and missions of robots (or intelligent mobile/vehicular devices). The sensors on each robot (i.e. green nodes and yellow DAs in Fig. 2) and sensors in machine swarm (i.e. orange nodes and red DAs in Fig. 2) may communicate through different wireless networks, and we consequently face a heterogeneous network structure among machines, in addition to heterogeneous network structure for wireless infrastructure and machines (green curve lines to wireless infrastructure and green nodes to yellow DAs; blue curve links to wireless infrastructure and orange nodes to red DAs).

With an overview on large sensor networks [13], there still exist a few fundamental questions worth further clarifications or investigations for M2M communications in this scenario.

1. To hop or not to hop for the body area network on each robots (green nodes and yellow DAs) (Fig. 3)
2. To hop or not to hop in machine swarm (orange nodes and red DAs)
3. When spectrum sharing is likely required, is it feasible to establish M2M communications in such complicated heterogeneous network structure?

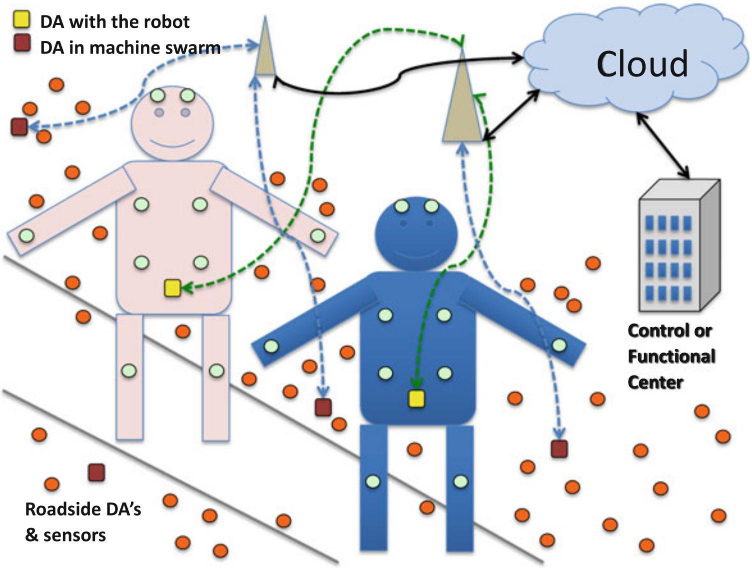

Fig. 2 Heterogeneous network architecture for wireless robotics

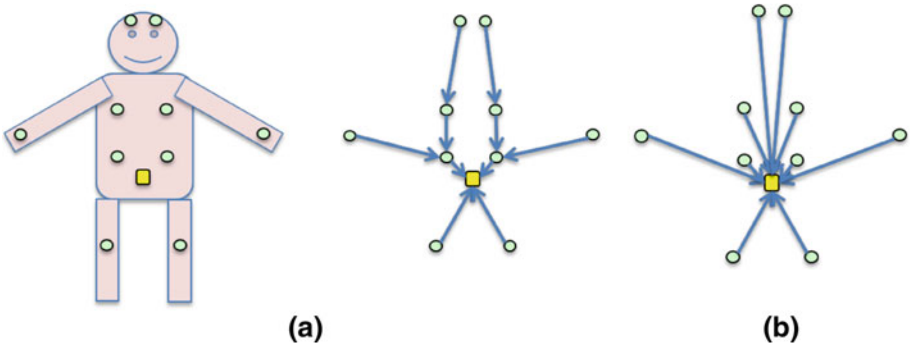

Fig. 3 **a** To hop or **b** not to hop for sensors with a robot. **a** Multi-hop ad hoc networking (from sensors to data aggregator). **b** One-hop star networking (from sensors to daa aggregator)

4. Any resource efficient network design under such a scenario of mobility and thus traffic (for robots)?

The first question can be considered in the following figure. Within the body area of a robot, the transmission range of all sensors to DA shall be facilitated the entire networking. Multi-hop is not necessary but mesh networking to extend reliability is useful. This is almost exactly like the networking for healthcare monitoring for an individual [13]. Appropriate medium access of star-type network topology seems working well, and mesh networking can be used to extend coverage. The second question is more complicated, to hop or not to hop in machine swarm. Among many pros and cons for each approach, we focus on the very fundamental issues. Due to the battery efficiency or energy harvest efficiency, sensors and machines must employ energy-efficient communication and networking, which inevitably suggests multi-hop ad hoc networking. However, successful operation of modern ad hoc networks relies on good (if not full) knowledge of end-to-end network information such as routing table etc. and consequently good amount of exchange of control packets and overhead [15], which limits applications on energy-efficient and spectrum-efficient wireless devices [11]. It is not difficult to show that just relying on multi-hop cooperative ad hoc networking results in long routing delay and even time-insensitive data traffic might be inappropriate, not to mention QoS, in M2M communications. Particularly, M2M communications for wireless robotics would not be able to stand for extremely long delay due to mobility and consequently location-dependent nature for data. To meet the requirement of time sensitive data transportation and QoS constraints for certain application such as video surveillance or navigation in wireless robotics, small-world network [16] can be employed to construct a new heterogeneous network structure using DAs as the access points to wireless infrastructure (like data highway), which not only can significantly reduce routing delay in the machine swarm, but also can meet QoS requirements by leveraging effective bandwidth and multi-path transmission [17].

A more interesting issue might be the third question. Large sensor networks are already fundamentally facing a lot of technology challenges [18]. Under spectrum sharing wireless networks or cognitive radio networks, whether to hop or not and subsequent networking issues have not been fully understood. The complicated mechanism relies on understanding of resulting interference analysis, in addition to traditional ad hoc networking. Such analysis has been studied in [19]. A further question is to understand connectivity in the large machine swarm as suggested in [18]. Under complicated interference analysis, an emerging technology known as stochastic geometry [20] is useful. A series of explorations to analytically characterize the connectivity of CRN and spectrum sharing ad hoc networks have been conducted [21]. As pointed in [18], connectivity plays a critical role in establishing large sensor and machine networks. It also demonstrates feasibility of spectrum sharing multi-hop networks. Rate and delay tradeoff can be enhanced by network coding, to ensure smooth operation of multi-hop networks [22]. Network cooperation is shown helpful in [23], and error control to improve network performance is also verified [24]. All these suggest us that multi-hop spectrum sharing with heterogeneous network architecture is feasible for machine swarm communications.

The last question is introducing another key factor, mobility, into network design. Sensor network to enable cyber-physical robotic systems emerges as an important subject in recent years [25–28], which involves robot routing, information packet routing, mobility, and data collection and fusion. In the following of this paper, we shall explore some important issues toward effective design.

3 Compress-and-Forward Information Collection in the Network of Correlated Sources

Almost all research in sensor networks and M2M communications assume rather static network topology. However, this is not true in wireless robotics. A robot moves based on information collection from sensors, due to the movement of this robot, the associated network topology is no longer static. It creates further problems for information collection from sensors to DA (i.e. robot) in multi-hop networking. As the DA is moving forward, the multi-hop data packets might trace behind robot, particularly under spectrum sharing to create extra delay due to waiting for spectrum availability. Spectrum efficient data collection from sensors is therefore a critical technology that has been overlooked in literature, and we will propose a novel technology based on in-network computation [29], beyond the widely considered data aggregation [30] or distributed source coding [31–34], in this section.

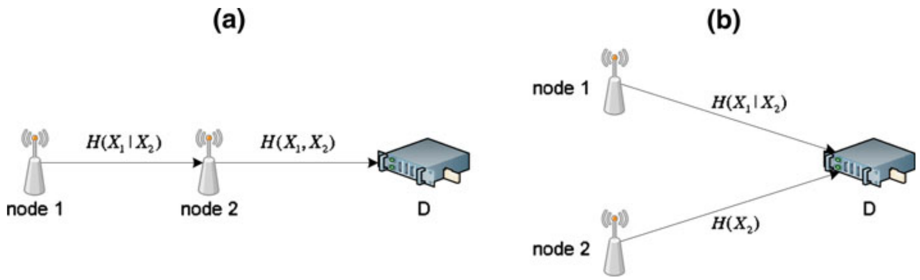

Fig. 4 The two cases of compress-and-forward transmission with its corresponding transmission flow. **a** Serial transmission. **b** Parallel transmission

3.1 Rationale of Compress-and-Forward Mechanism

Noting nature of machine to machine (M2M) [35] and wireless sensor network (WSN)[31], the observed information between source nodes are likely correlated. Efficiently transmission and distributed encoding of observed information becomes essential especially when the network size becomes larger. Distributed source coding rate region of joint correlated sources was originally studied by Slepian and Wolf [32], and numerous subsequent efforts [34,36] extend the study into network information flow. Based on type of information transmission, we conclude two basic types of information forwarding: serial and parallel, as shown in Fig. 4. In Fig. 4, two source nodes with source $(X_1, X_2) \sim f(x_1, x_2)$ encoded with rate R_1, R_2 to destination node D with two different ways, the optimal rate to lossless is also different. In case (a) the encoding rate $R_1 > H(X_1|X_2)$, $R_2 > H(X_1, X_2)$ is achievable and optimal while in case (b), a typical example of Slepian–Wolf, the optimal rate could be $R_1 > H(X_1|X_2)$, $R_2 > H(X_2)$.

In Fig. 4 the encoding rate is obviously achievable. But in parallel transmission case, the optimal rate may be practical by the feature of wireless communication that every transmission forwarded via same medium, i.e. side information can be obtained by *overhearing*. In this way, nodes do not merely encode and forward observed information, a more efficient data compression rate may be applied by overhearing and relaying information, and we call this "compress-and-forward" transmission. In this work we assume the compress-and-forward method is done perfectly, that is, the optimal rate is applied to source once information overhearing is done.

The network layer information flow with correlated source is complicated. Traditional works [34,36] on rate region of correlated source in network layer model the problem as optimization problem subject to Slepian–Wolf coding rate and flow conservation rule, i.e. incoming flow shall be equal to outgoing flow. When we consider that compress-and-forward strategy is applied, however, the flow conservation flow is incorrect. The outgoing flow of source X_1 gets efficiently $H(X_1|X_2)$ with overhearing information of source X_2. Therefore the flow conservation rule may be complete if we take the overhearing information into consideration. Overall, we modify the rule conservation rule by treating the overhearing information a special form, and the compress-and-forward strategy can be reasonably modeled.

We hereafter assume the compress-and-forward method is applied, and encoding rate perfect utilizes overhearing information, one remaining issue is that how to efficiently forward information to destination, i.e. the routing strategy. In compress-and-forward method, the routing mechanism influences the overall transmissions, as shown in Fig. 5. In Fig. 5,

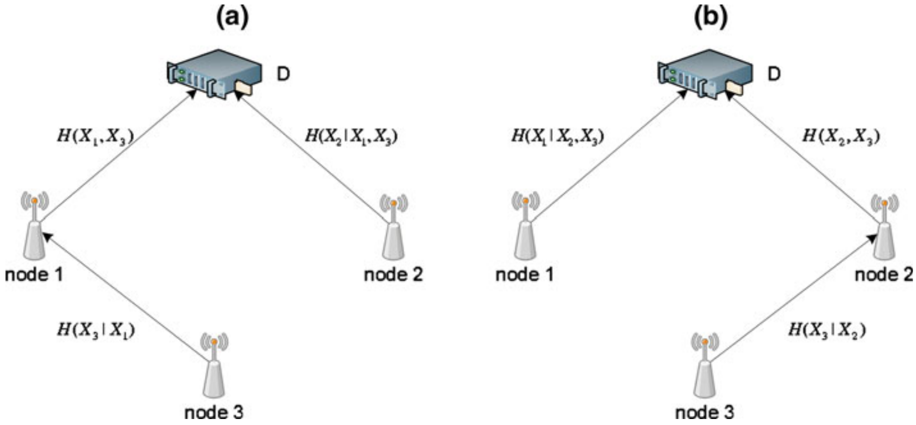

Fig. 5 In case **a** and **b** with different forwarder of node 3, the total transmission will be different. **a** Node 3 choose node 1 to be forwarder, and node 2 can overhear the two transmission flows. **b** Node 3 choose node 2 to be forwarder, and node 1 can overhear the two transmission flows

there are three source nodes with correlated sources $(X_1, X_2, X_3) \sim f(x_1, x_2, x_3)$ encode with rate R_1, R_2, R_3 to destination node D. Observed information of node 3 shall be forwarded via node 1 or 2 and overhearing information is attainable between node 1,2. We can see in case (a) that information of source X_3 is via node 1, an achievable rate is $R_1 > H(X_1, X_3)$, $R_2 > H(X_2|X_1, X_3)$, $R_3 > H(X_3|X_1)$. While in case (b) an achievable rate is $R_1 > H(X_1|X_2, X_3)$, $R_2 > H(X_2, X_3)$, $R_3 > H(X_3|X_2)$ if node 2 is chosen. Suppose transmission rate guarantees lossless if inequality meets. The overall transmission flow of observed data is different in these two cases, i.e. the network routing strategy plays an important role to overall transmission flow. In this way, based on that compress-and-forward is done perfectly, we seek for an optimal routing algorithm that efficiently routes correlated source to destination with losslessly recovery of source.

In subsection B, we give an overview of notation and network model setup, and then formulate the efficient transmission flow problem as an optimization problem while wireless overhearing information is taken into consideration. The optimal routing algorithm is given in subsection C after a brief introduction of the algorithm, Gibbs sampler. Subsection D we give the simulation result.

3.2 Network Model

In this clause we construct the network model discussed in this work. A graph $G = (V, E)$ represents the network where V is the set of all nodes while E the set of all edges. A set of source nodes $S \in V$, $S = 1, 2, \ldots, N$ is given and a destination node $D \in V$. Edge $e_{ij} \in E$ exists iff $j \in V$ is within transmission range of $i \in V$. For node $i \in V$, the neighboring nodes set $N(i)$ is defined $N(i) = j : \forall j \in V, e_{ij} \in E$. The set of sources $\mathbf{X} = \{X_1, X_2, \ldots, X_N\}$ is assumed such that source X_i is discretely and memorylessly observed by source node $i \in S$. A joint distribution $p(x_1, x_2, \ldots, x_N)$ is also given that each value of source is drawn i.i.d. from the distribution.

The observed information from each source node is encoded and routed to destination D such that D can recover the original source losslessly. Source node is allowed to route information, and for node $i \in S$, the observed and relayed information is routed from $i \in V$

to one of its neighboring node $o(i) \in N(i)$. Note that $D \in N(i)$ for some i, in this case, node i can forward the observed and relayed information to destination.

In a transmission link $e_{ij} \in E$, the transmission flow f_{ij} is defined as the sufficient information that shall be transmitted by node i so that all information, observed or relayed, can be error-free transmitted. The physical transmission data is correlated but not equal to flow. By routing mechanism, $f_{ij} > 0$ iff $j \in V$ routes information received from $i \in V$, and we denote $j = o(i)$. A feasible flow set $\{f_{ij}|i, j \in V; j = o(i), \forall i\}$ is referred to a set of flow on each transmission link that D can losslessly recover the total source information by $\{f_{iD}|D = o(i), \forall i \in V\}$. Note that by compress-and-forward mechanism, a source node $i \in S$ forwards observed information as well as relayed information, i.e. $f_{ji}, \forall j : o(j) = i$. Since flow is conserved to each node, we have the flow conservation rule usually formed as Eq. (1) [34]

$$\sum_{j:,e_{ij}\in E,o(i)=j} f_{ij} - \sum_{j:e_{ji}\in E,o(j)=i} f_{ji} = \pi(i), \quad \forall i \in V, \tag{1}$$

$$\text{where } \pi(i) = \begin{cases} H(X_i), & \text{if } i \in S \\ -H(X_1, X_2, \ldots, X_{N_S}), & \text{if } i = D \\ 0, & \text{otherwise.} \end{cases}$$

Here we assume $f_{ij} = 0$ if $i = D$. As we illustrate in introduction, the flow conservation rule is not satisfied in wireless network due to compress-and-forward mechanism and overhearing information. To differentiate the transmission and overhearing link, we define an edge indicator t_{ij} defined over edge $e_{ij} \in E$ and $t_{ij} = 1$ iff $o(i) = j, \forall i \in V$ and $t_{ij} = 0$ otherwise. We call it transmission link if $t_{ij} = 1$, and overhearing link otherwise. According to the routing mechanism we have $\sum_{j:(i,j)\in e_{ij}} t_{ij} = 1, \forall i \in V$. An essential mechanism of compress-and-forward is that a node i can perform better encoding by the all overhearing information $\sum_{t_{ji}=0,\forall j} f_{ji}$. Traditionally the flow f_{ij} considers the information flow on $e_{ij} \in E$ with $t_{ij} = 1$, the inconsistence of flow conservation rule is hence resulted by the overhearing information. A simple example shown in Fig. 4 that, for node 2 a better encoding can be performed by overhearing information from node 1, leading to reduction from observed information $H(X_2)$ to forwarded information $H(X_2|X_1)$ and the reduction is exactly the mutual information. The total information flow that node i has to transmit without overhearing information is the total incoming flow $\mathbf{X_i} = \sum_{t_{ji}=1,\forall j} f_{ji}$, and hence the necessary information flow for node i to transmit would be $H(\mathbf{X_i})$. If the overhearing information flow is also applied to compress-and-forward mechanism, the coding performance efficiency advised by overhearing information flow would be the mutual information between $\mathbf{X_i}$ and the overhearing information by node i, as a compensation flow. Referring to Fig. 4, if the overhearing information from node 2 results in a equivalently negative flow $I(X_1; X_2)$, the flow conservation rule would be satisfied in node 1. A more complicated example is shown in Fig. 6. In Fig. 6 there are 4 source nodes with correlated source $\{X_1, X_2, \ldots, X_4\}$ and one destination node D. If the routing pathes is already given where the dotted lines represent the overhearing links and the real lines represent the transmission links, we can compute the compensation flow and the necessary information flow in each transmission link. The incoming flow at each node would be equal to the necessary transmission flow, and the flow conservation rule would be modified to be satisfied.

By modifying the conservation law of flow, the constraint of flow has been established. In the following, we formulate the problem formally as an optimization problem. Since every source node routes a transmission path to D, the overall network structure is obviously a spanning tree with root D. If transmission flow f_{ij} on $e_{ij} \in E$ is considered as the cost while

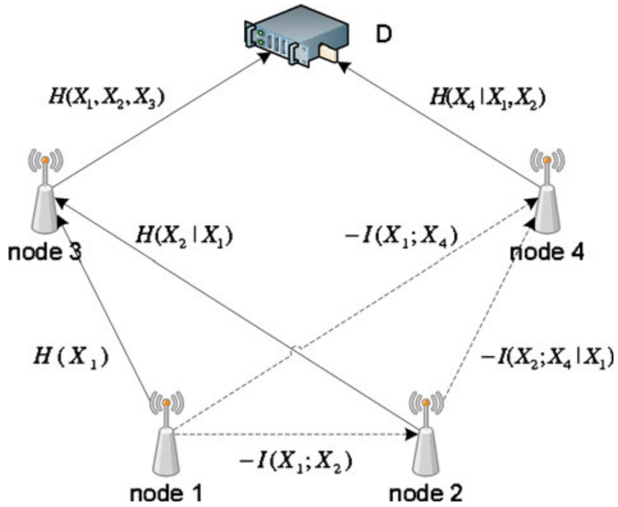

Fig. 6 With adding of compensation flow, the flow conservation rule is satisfied

$t_{ij} = 1$, and we define the optimal feasible flow set $\{f_{ij}\}$ as the minimum total flow, i.e. $\sum_{t_{ij}=1,\forall e_{ij}\in E} f_{ij}$, the original problem is hence to find a minimum spanning tree while the cost is varied as the tree structure.

We therefore formulated the problem as follows:

$$\min_{t_{ij}} \sum_{(i,j)\in E} t_{ij} f_{ij}$$

$$\text{subject to} \quad t_{ij} \in 0, 1, \quad \forall (i,j) \in E \tag{2a}$$

$$\sum_{(i,j)\in E} t_{ij} = |V| - 1, \tag{2b}$$

$$\sum_{(i,j)\in\{B,B\}} t_{ij} \le |B| - 1, \quad \forall B \subseteq E \tag{2c}$$

$$f_{ji} = I(\mathbf{X_i}; \mathbf{X_j}), \quad \forall (i,j) \in E, t_{ij} = 0 \tag{2d}$$

$$\sum_{j:(i,j)\in E} f_{ij} - \sum_{j:(i,j)\in E} f_{ji} = \pi(i), \quad \forall i \in V, \tag{2e}$$

$$\text{where } \pi(i) = \begin{cases} H(X_i), & \text{if } i \in S \\ H(X_1, X_2, \ldots, X_{N_S}), & \text{if } i = D \\ 0, & \text{otherwise.} \end{cases}$$

Note that subject function (2a)–(2c) are the constraints of forming a spanning tree, and by subject function (2d) and (2e) the flow of transmission links, i.e. $t_{ij} = 1$, can be found. The flow over overhearing link is modified to meet the flow conservation rule.

The minimum spanning tree is a classical NP problem. In addition to find a routing mechanism to achieve optimal feasible flow set, we want the routing mechanism to be distributed since central controlling is too complex and resource-inefficiency. Hence we introduce a distributed routing algorithm leading to optimal feasible flow based on routing-and-forward mechanism in next subsection.

3.3 Optimal Routing for Packets

In this subsection we propose a distributed routing algorithm that each node $i \in V$ can individually select a node $j = o(i)$ to forward the necessary information flow f_{ij} and the total information flow set $\{f_{ij}\}$ achieves optimal. Before the proposal of algorithm we give a brief introduction of the background, the Gibbs sampler. Further understanding can be referred to [37].

3.3.1 Gibbs Sampler

For a graph $G = (V, E)$ with node set V and edge set E, we define node $i \in V$ a state $\lambda_i \in \Lambda$ where $\Lambda = \{1, 2, \dots, |\Lambda|\}$ is a configuration state set. The configuration of graph is defined as $\Lambda^{|V|} = \{\lambda_1, \lambda_2, \dots, \lambda_{|V|}\}$ where $|V|$ denotes the number of nodes. For a node subset $c \in V$, the potential function V_c defined by the state of nodes, i.e. $\Lambda_c = \{\lambda_i : i \in c \subseteq V\}$, is associated with a real value $V_c(\Lambda_c) \to \mathbb{R}$ iff c is a clique, otherwise the value is 0. A energy function E defined within a node subset $B \subseteq V$ is valued related to the potential function that

$$E(\Lambda_B) = \sum_{c:c\subseteq B} V_c(\Lambda_c). \tag{3}$$

The total energy of the entire graph is hence $E(\Lambda^{|V|})$ and related to the configuration of graph. At each state transition procedure, a node $i \in V$ changes state to state λ_i according to the Gibbs distribution $\pi_i(\lambda_i)$ related to the local energy $E(\lambda_i)$ that

$$\pi_i(\lambda_i) = \frac{1}{Z_T} e^{\frac{-E(\lambda_i)}{T}}, \tag{4}$$

where $Z_T = \sum_{\lambda_i \in \Lambda} e^{\frac{-E_i(\lambda_i)}{T}}$ is a normalization constant, and $T > 0$ is a temperature parameter. The local energy for $i \in V$ is associated to the energy function of clique where node i belongs to. i.e. $E(\lambda_i) = \sum_{c:i\in c} V_c(\Lambda_c)$. Since the local energy function of node i is defined within clique containing i, the state transition is hence related to nodes adjacent to i only.

For Gibbs sampler in every state transition procedure, node i changes to state λ_i according to Eq. 4. If the temperature parameter is logarithmically decreasing with procedure iteration time t, usually formed as $T = \frac{T_0}{\log(2+t)}$ where T_0 is a constant, and neighboring nodes do not transit state simultaneously, the total energy of the graph $E(\Lambda^{|V|})$ will approach minimum as $t \to \infty$. The priority of node performing state transition can be any given, e.g., transited in order of sequence.

Since the node performing state transition procedure in Gibbs sampler is related to neighboring nodes only, i.e. local energy is needed merely, the state transition procedure can be performed distributed. We do some modifications to the Gibbs sampler to meet our purpose and propose the routing algorithm to achieve optimal feasible flow set in next subsection.

3.3.2 Routing Algorithm

In this subsection, we modify the Gibbs sampler described before to meet our problem and then propose the routing algorithm. The state configuration here is modeled as the $forwardingstatus$ of each node, i.e. each node is endowed as one of its own configuration state $\lambda_i \in \Lambda_i = \{1, 2, \dots, |N(i)|\}$, where $|N(i)|$ is total number of neighboring nodes of i. For simplified we denote λ_i as $o(i)$. The potential function is only defined on node and its forwarding node, i.e. $V_c(\Lambda_c) = f_{ij} \forall c = (i, j) : t_{ij} = 1$ and $V_c(\Lambda_c) = 0$ otherwise. The energy function over the entire network state configuration $\Lambda^{|V|} = \{o(1), o(2), \ldots, o(N)\}$ would be the total transmission flow $\sum_{t\,ji=1, \forall e_{ij} \in E} f_{ji}$.

By the concept of compress-and-forward mechanism, each node performs efficient encoding by the overhearing information. We assume the overhearing information comes from neighboring nodes, and node i transmits sufficient information flow $f_{io(i)}$ by overhearing information from its forwarding node $o(i)$ separately. The probability of selecting $\lambda_i \in N(i)$ as forwarding node is according to the Gibbs distribution

$$\pi_i(\lambda_i) = \frac{1}{Z_T} e^{\frac{-f_{i\lambda_i}}{T}}, \tag{5}$$

Overall we model the potential function as the transmission flow, and the configuration state set is node related. By [37], the total energy of graph, i.e. the total sufficient transmission information flow here, will approach minimum $t \to \infty$. Therefore we propose the routing algorithm as follows:

Algorithm 1 GIBBS

1: Calculate the temperature constant $T = \frac{T_o}{log(2+t)}$ at time t.
2: By the overhearing information of its forwarders, node i compute the sufficient flow f_{ij} to the possible forwarder j based on compress-and-forward scheme.
3: Calculate the transition probability $\pi_i(\lambda_i)$ according to the sufficient transmission flow to each possible forwarder of node i, and choose a forwarder according to the distribution π_i.

3.4 Simulations

In this subsection we run simulation to perform the efficiency of our proposed algorithm. The performance of Gibbs algorithm is compared to greedy algorithm, i.e. each node selects the node that cost least to transmit as its forwarder rather than according to Eq. 5. As greedy algorithm is a well-known local optimal algorithm, we can see that our algorithm get better performance through comparison with greedy algorithm both based on local approach.

In our simulation, we set N source nodes uniformly distributed in a unique square, and set the destination node D in the middle of the square. For source nodes i, j, edge e_{ij} exists iff they are within transmission range. Every node selects one node within the transmission range as its forwarder to transmit observed information to D.

The joint Gaussian model is assumed for the data sensed by source nodes. For source nodes $S = 1, 2, \ldots, N$ the observed information is denoted as random vector $\mathbf{Z} = (Z_1, Z_2, \ldots, Z_N)$. According to [34], the pdf of observed data is assumed to be

$$f(z_1, z_2, \ldots, z_N) = \frac{1}{\sqrt{2\pi}^N \sqrt{\det(C_{ZZ})}} \times \exp\left(-\frac{1}{2}(\mathbf{Z} - \mu)^T C_{ZZ}^{-1}(\mathbf{Z} - \mu) \right),$$

where C_{ZZ} is the covariance matrix of observation, and we set the correlation model $C_{ZZ}(i, j) = \sigma^2 e^{-cd_{ij}^{\beta}}, \forall i \neq j$ and $C_{ZZ}(i, i) = {\sigma_i}^2, \forall i$. d_{ij} is distance between nodes i and j, and we set the parameter $c = \beta = 1$ also.

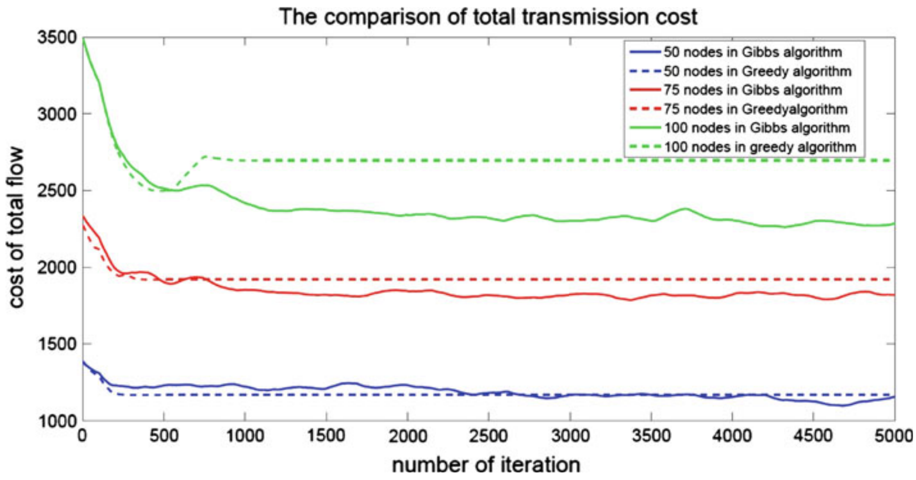

Fig. 7 The simulation result of Gibbs algorithm compared with greedy algorithm

Assume the sources are independently quantized as samples with same quantization step Δ which is sufficiently small, and the quantize random vector $\mathbf{X} = (X_1, X_2, \ldots, X_N)$ such that $H(\mathbf{X}) = H(\mathbf{Z}) - N \log \Delta$. Therefore the conditional entropy shall be

$$H(X_B|X_{B^c}) \approx \frac{1}{2} \log \left((2\pi e)^{N-|B^c|} \frac{\det(C_{ZZ})}{\det(C_{Z_{B^c}} C_{Z_{B^c}})}\right) - (N - |B^c|) \log \Delta, \tag{6}$$

where B is an subset of source and B^c represents complement. The conditional entropy would be used as feasible flow in compress-and-forward method.

In simulation 1 we alter the number of source nodes to 50, 75 and 100 while correlation parameter $\sigma^2 = 1$ is fixed. In each iteration a node chooses forwarder with different algorithms, Gibbs or greedy, and the total sufficient transmission flow required to ensure losslessly decoded at destination node is calculated according to Eq. 6. The simulation result is shown in Fig. 7. In Fig. 7 we can see that basically more sources leads to more total amount of transmission flow. The greedy algorithm is easily stick into local optimization condition, while the we can see that the Gibbs algorithm gets better performance as time goes by and the improvement increases as number of source nodes increases. When 100 source nodes is deployed, Gibbs algorithm gets around 17 % improvement.

In simulation 2 the total number of source node is fixed as 100, but the correlation parameter σ^2 is variant to 0.4, 0.7 and 1. The simulation result is shown in Fig. 8. We can see that Gibbs algorithm achiever a better performance than greedy around 10, 15 %, and the higher correlation of source of gets higher performance. In this simulation we can also see that when $\sigma^2 = 0.7$ greedy algorithm converges to a larger total transmission flow than $\sigma^2 = 0.4$, which is object to common sense. The total amount of transmission flow is also decreased as time goes on.

As mobility of wireless robotics introduces more critical challenges in communication efficiency, we leverage the broadcasting nature of wireless communications to implement in-network computation, and successfully to trade communication efficiency, and subsequently less interference due to mobility in wireless robotics.

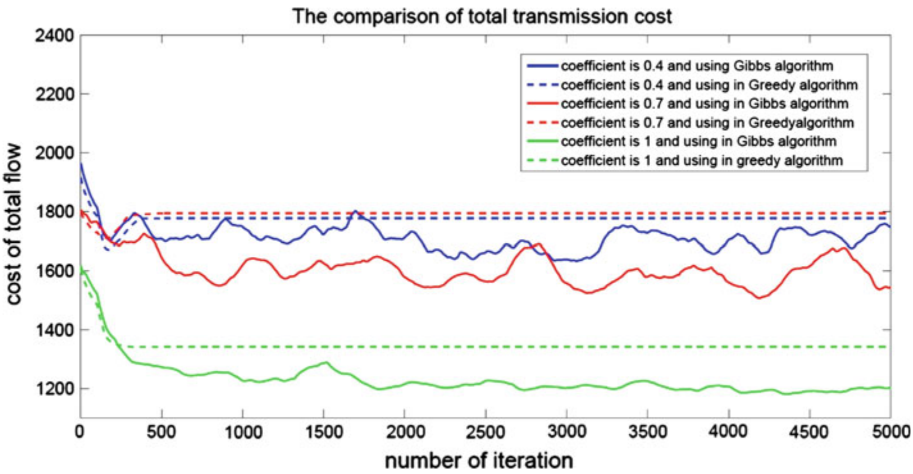

Fig. 8 The simulation result of Gibbs algorithm compared with greedy algorithm

4 Coverage of Service

To complete the consideration of M2M communications for wireless robotics, we have to further look into some more practical issues. In case the machines are randomly scattered in the swarm, the coverage strong affects how system functions. We construct mathematical model to find the coverage formula of the swarm by random deployment and discuss the inefficiency due to the randomness of deployment. Mobility invokes new challenges [38,39]. Then, we discuss the effect of the availability of machines due to low battery of sensor or the randomness of environment, and explore the philosophy of machine supplement. Finally, we use a simple illustration to show the importance of coverage of machines/sensors, and thus percentage of time for service availability due to coverage.

4.1 Coverage and Device Management in Machine Swarm

In a general heterogeneous architecture for wireless robotics, see Fig. 2, machines in the swarm can gather useful information from the environment and communicate with robots to facilitate their missions. Proper coverage of the sensors will guarantee a more accurate and extensive information from the environment and also, has more opportunities for communication. While low coverage will induce more miss detections and communication failures. In other M2M scenario, like sensor networks for detection of fire in a forest[40] or for detection of intruders in a battlefield [41], high coverage can both provide a higher benefit. In general, coverage is usually important in most networks, although they may have different meanings depending on the context [42]. In the following subsection, we will discuss the issues regarding of coverage by randomly deployment and its relation to some aspects of quality of service of a system (QoS).

We use two factors to construct the model of network of machine swarm: random deployment and communication ability of machines, device management by considering the failure effect of each machine, while such failure effect can arise from the uncertainty of environment or exhausted energy in a machine.

Since the deployment of machine in swarm is random, we recognize the Boolean model from stochastic geometry is suitable for our scenario [43]. Our model will base on it with a few extensions. Let the model be defined as follows. Define the region of interest (RoI) to be the region where machines being deployed, and let the area of RoI be β. The locations of machines in the RoI follow a Poisson Point Process (PPP). The density of the PPP λ is just the density of the machine. Each machine in the swarm has a sensing area and a communication area. Machine can sense information from the area within its sensing area and can communicate with robots or other sensors/machines within its communication area. Assume each machine is omnidirectional with sensing area being a circle with radius r centered at it. For simplicity, we assume the communication area and sensing area are identical for each sensor. In summary, the three elements β, λ and r together establish the swarm model.

Due to the uncertainty of environment or exhausted energy of machine, machines in swarm will break down over time, which is a critical device management issue. To model the situation, we assume each machine has i.i.d. lifetime hazard function which is $-\ln(1-p)$ per unit time (so it will break down in one unit time with probability p).

4.2 Coverage Volume Fraction (CVF)

In this subsection, we turn to formally define the coverage, and we discuss inefficiency of uniform random deployment. Then we explore the coverage maintenance against malfunction of machines. The coverage region be defined as the union of all the machines sensing area, then the coverage volume fraction (CVF) is defined as the fraction of the area of the sensing region to the area of the region of interest. We have the following proposition for CVF in our model.

Proposition 1 *Let N_{PPP} be the deployed machine number, then the CVF is approximately*

$$CVF \cong 1 - e^{-\lambda \pi r^2} = 1 - e^{-\frac{N_{PPP}}{\beta}\pi r^2} \tag{7}$$

if β is large enough.

Proof This is a straightforward result from stochastic geometry, for example, see [44].

In a typical problem of coverage maintenance, the QoS requirement is that we need to maintain a coverage fraction (CVF) above a level γ all the time. Relevant research usually includes energy saving protocol [45,46], while we focus on the required number of supplementary machines against malfunction machines by different supplement methods. Coverage will decay and be below the QoS requirement due to failure of some machines. So, we need to supplement machines. Machine has a failure probability p per unit time. In order to maintain coverage fraction in one unit time, we cannot simply deploy machine with number given by Eq. (7). We must foresee the effect of machine failure. The virtual density of machine swarm is only $(1-p)\lambda$. To achieve coverage fraction γ, we need to deploy $N_{PPP}(p)$, where p stands for the failure probability per unit time.

$$N_{PPP}(p) = -\frac{\beta}{\pi r^2}\ln(1-\gamma) \times \frac{1}{1-p} \tag{8}$$

Consider the theoretical ideal case for deployment, i.e, the failure probability of machine is zero, and every deployed machine's sensing area is non-overlapping, then we can achieve zero waste of machine resource for coverage and only need a lower bound required number of machine, $N_{non-overlapping} = \frac{\beta}{\pi r^2}\gamma$, to achieve coverage fraction γ. Equation (8) can be simplified to

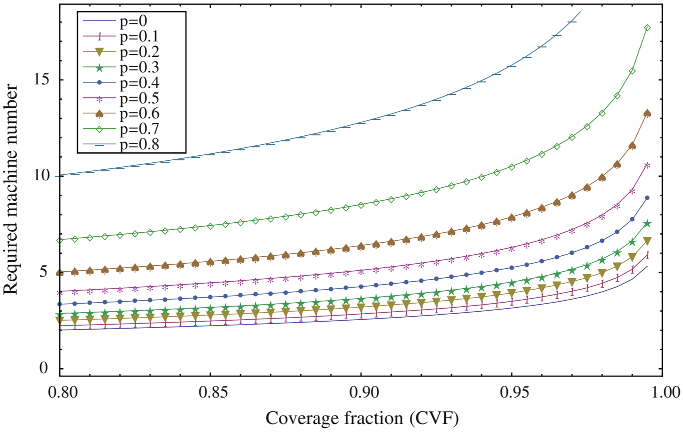

Fig. 9 Required machine number by PPP versus coverage fraction under different failure probability p. The numbers have been normalized by the required number of ideal non-overlapping deployment under zero failure probability

$$N_{PPP}(p) = -N_{non-overlapping}\frac{\ln(1-\gamma)}{\gamma} \times \frac{1}{1-p} \tag{9}$$

This suggest us to define the over-deployment factor. □

Definition 1 Define the over-deployment factor $k(\gamma, p)$ to be the ratio of required machine number by PPP to required machine number by theoretical non-overlapping deployment. So

$$k(\gamma, p) = -\frac{\ln(1-\gamma)}{\gamma} \times \frac{1}{1-p} \tag{10}$$

The over-deployment factor indicates the required number of deployment compared to the ideal deployment, i.e. no failure probability and no overlapping machine. It is generally a function of failure probability and required coverage fraction. In Fig. 9, we plot required machine number by PPP versus coverage fraction under different failure probability. As shown in Fig. 9 for every failure probability (even for zero failure probability), the required number becomes extremely large for high coverage, while the required number also increases as the failure probability. It is observed that the differences of the required number among different failure probability are small for low failure probability while it is large for large failure probability. Thus, two factors contributes greatly to the deployment cost of machines, one is the high coverage requirement, and the other is high failure probability. In this subsection, we will discuss these two problems separately and, respectively.

Intuitively, uniform PPP deployment is not inefficient for low CVF, so a natural question arises to identify an appropriate threshold for PPP maintaining an efficient deployment. We first define the Critical Machine Number, $N_{PPP,critical} = \frac{\beta}{\pi r^2}$, as the critical machine number in our swarm model, we then immediately have the following,

Proposition 2 *The increasing percentage of CVF and deployed machine number N_{PPP} have the following relation*

$$\frac{dCVF}{CVF} = \frac{\frac{N_{PPP}}{N_{PPP,critical}}}{e^{\frac{N_{PPP}}{N_{PPP,critical}}} - 1}\frac{dN_{PPP}}{N_{PPP}} \tag{11}$$

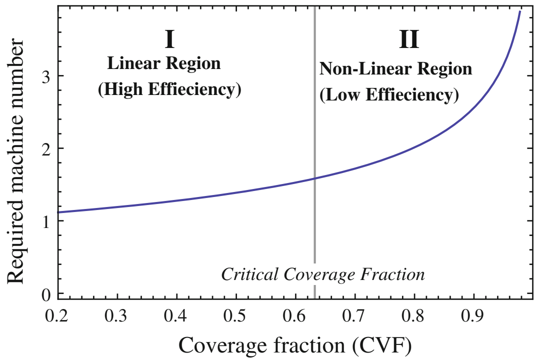

Fig. 10 Required machine number by PPP versus coverage fraction under zero failure probability. The numbers have been normalized by the required number of ideal non-overlapping deployment under zero failure probability

By Proposition 2, for $N_{PPP} << N_{PPP,critical}$, $\frac{dCVF}{CVF} \simeq \frac{dN_{PPP}}{N_{PPP}}$, while $\frac{dCVF}{CVF} \simeq 0$. Thus, when our deployed machine number is larger than the critical machine number, or equivalently, when we need our coverage larger the critical coverage fraction $1 - e^{-1} \simeq 63.21\,\%$, the efficiency of PPP deployment decays very rapidly. Unfortunately, in many cases, the coverage is needed for a percentage larger than the critical coverage fraction, 63.21 %. In Fig. 10 we summarize the idea of Proposition 2 by plotting the required machine number versus coverage fraction under zero failure probability. In Fig. 10 critical coverage 63.21 % divide the deployment by PPP into two regions. Below 63.21 % the region is approximately linear representing high efficiency while above it the region is nonlinear representing low efficiency. This suggests further modification of random deployment is needed. For example, by providing the power and algorithm of self-configuration of machines or to use a non-uniform random deployment.

Now we turn to device management under device failure probability. In many situations, the QoS is required to maintain a coverage fraction (CVF) above a level γ all the time. We have to supply extra machines/sensors given that each machine has a failure probability p per unit time. Initially, we deploy N_0 machines to achieve coverage fraction γ, but coverage decays and thus is below the required level due to the failure of some machines. To maintain coverage, we should supplement machines n times per unit time. This motivates the definition of Supplement Rate as follows.

If we supplement machines per $\frac{1}{n}$ unit time, then the supplement rate is defined to be n. Given supplement rate n, there is a minimum number ΔN_n we shall supplement in total in one unit time. Figure 11 illustrates this idea.

Recall that the lifetime hazard function of each machine is $-\ln(1-p)$ and i.i.d., we have

$$\Delta N_n = n\Big((1-p)^{\frac{-1}{n}} - 1\Big)\frac{\beta}{\pi r^2}\Big(-\ln(1-\gamma)\Big) \tag{12}$$

Since $\Delta N_{supplement,n}$ is decreasing with n, we can reduce the total supplement amount by increasing the supplement rate. However, there is a theoretical lower bound N_{Lower} by increasing the supplement rate.

$$\Delta N_{Lower} = (-\ln(1-p))\frac{\beta}{\pi r^2}(-\ln(1-\gamma)) \tag{13}$$

Finally, although raising supplement rate will reduce the additional deployed machine amount while maintaining the CVF above a desired level γ, the time averaged CVF will also be reduced, i.e. the time average CVF by supplement rate n is defined by $\lim_{T\to\infty} \frac{1}{T}\int_0^T CVF(t)dt$ and we have

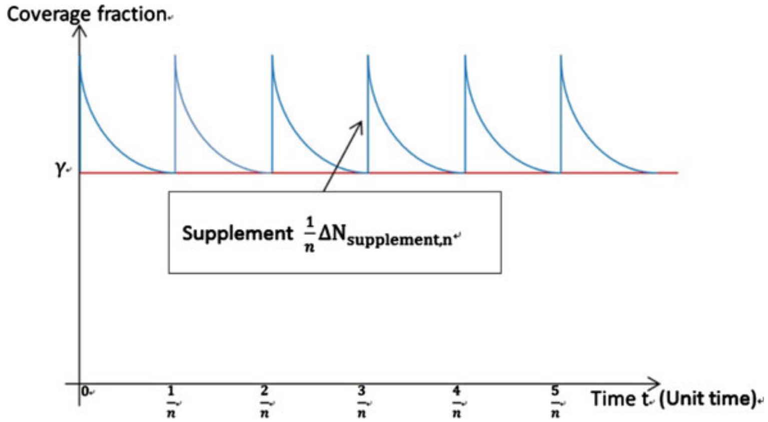

Fig. 11 The γ is the coverage fraction level we want to maintain all the time, so we supplement machines by the number $\frac{1}{n}\Delta N_n$ per $\frac{1}{n}$ unit time

$$\lim_{T\to\infty}\frac{1}{T}\int_0^T CVF(t)dt = 1 - n\int_0^{\frac{1}{n}}(1-\gamma)^{(1-p)^{\frac{-1}{n}+t}}dt \tag{14}$$

Device management can be viewed as a trade-off between number of deployed machines and the time averaged CVF.

4.3 Cooperation among Multiple Operators

An practical problem considering the feasibility of machine swarm network is the huge cost of machine deployment for each operator of machines. A cooperation of machine deployment among multiple operators is thus desirable. However, due to the selfish nature of operators, i.e. they want to optimize their benefits only, the cooperation must give enough incentives for each operator. We can therefore model this situation by a cooperative game and using the Shapley Value method to obtain a fair cost sharing rule. We use a simple example to illustrate this idea. Let the cooperation between different operators by a cooperative game [47], which consists of

- Player set $\mathbb{N}$: The set of operators, indexed by $1, 2, \ldots, N$
- Characteristic function C : A real function of any subset of $\mathbb{N}$ which gives the total cost of any coalition of operators formed by the subset of $\mathbb{N}$
- Imputation $\mathbf{x}$: A real vector $\mathbf{x} = [x_1, x_2, \ldots, x_N]^T$ satisfying

  1. $\sum_{i\in\mathbb{N}}\mathbf{x}_i = C(\mathbb{N})$
  2. $\mathbf{x} \le C(\{i\})\ \ \forall i \in \mathbb{N}$

  which represents a cost sharing rule for the grand coalition (coalition formed by all operators) such that the cost share is lower than the cost for deploying alone for each operator.

The cost of a coalition is defined as the total sum of number of sensors needed to be deployed in every region. Mathematically speaking, the cost is constructed by the following steps:

- There are M different regions, represented by $A_i, i = 1, 2 \ldots, M$, each with area $\|A_i\|$
- The required coverage vector $\alpha_i = [\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{iM}]^T$ denotes the desirable coverage (inelastic QoS) in each region for operator i
- By using the coverage formula, the cost for operator i to deploy alone is $C(\{i\}) = \sum_{j=1}^{M} -\ln(1-\alpha_{ij})\frac{\|A_j\|}{\pi r^2}$
- The total cost of of a coalition $\mathbb{S} \subseteq \mathbb{N}$ is equal to the sum of largest required number of sensors in each region, which is $C(\mathbb{S}) = \sum_{j=1}^{M} -\ln(1-\max_{i\in\mathbb{S}} \alpha_{ij})\frac{\|A_j\|}{\pi r^2}$

Now the problem is how to choose a cost sharing method which is denoted by a vector $\mathbf{x}$ with component x_i representing the cost share of operator i. Since the sharing rule should pass the stability criteria in the sense that once an operator joins the grand coalition, this operator will not leave the coalition, and the efficiency criteria, i.e. the sum of cost share is equal to the total cost. Mathematically speaking, the designed sharing rule $\mathbf{x}$ should satisfy

$$\sum_{i\in\mathbb{S}} \mathbf{x}_i \leq C(\mathbb{S}) = \sum_{j=1}^{M} -\ln\left(1-\max_{i\in\mathbb{S}} \alpha_{ij}\right)\frac{\|A_j\|}{\pi r^2} \qquad \forall \mathbb{S} \subseteq \mathbb{N} \tag{15}$$

$$\sum_{i\in\mathbb{N}} \mathbf{x}_i = C(\mathbb{N}) = \sum_{j=1}^{M} -\ln\left(1-\max_{i\in\mathbb{N}} \alpha_{ij}\right)\frac{\|A_j\|}{\pi r^2} \tag{16}$$

The notion of above criteria is called the core [48] which is a central concept in coalitional games. However, the sharing rule satisfying above criteria is not unique. So a criteria refinement is required for a deeper analysis. We use following three additional criteria refinements.

1. Symmetry: if two different operators have exactly the same required coverage vector α, then their cost share should be the same
2. Fairness: an operator with higher coverage requirement should absorb more cost
3. Flexibility: the sharing rule of different regions can be derived separately, so if operators want to negotiate a cooperation contract for a new region in the future, they could focus on the new contract while ignoring the past contract history.

A theory from coalitional game shows that the solution exists and is unique, which is given by the so called Shapley Value [49],

$$\mathbf{x}_i = \sum_{\mathbb{S}\subseteq\mathbb{N}; i\in\mathbb{S}} \frac{(N-|\mathbb{S}|)!(|\mathbb{S}|-1)!}{N!}[C(\mathbb{S}) - C(\mathbb{S}-\{i\})] \;\; \forall i \in \mathbb{N} \tag{17}$$

where $|\mathbb{S}|$ is the number of operators in the coalition $\mathbb{S}$.

By [50], a simple algorithm gives the formula of the Shapley Value,

1. assume there are there are n_{jk} operators with coverage requirement β_{jk} in A_j and different required coverage in region A_j is sorted by
$$0 = \beta_{j,0} < \beta_{j,1} < \beta_{j,2} < \cdots < \beta_{j,m_j}$$
2. Let $s_k = \sum_{i=k}^{m_j} n_{ji}$, representing the number of operators with coverage requirement greater or equal to β_{jk} in region A_j, then the Shapley Value of operator l is
$$\sum_{j=1}^{M}\sum_{k=1}^{i} \frac{\|A_j\|}{\pi r^2 s_k} \ln\left(\frac{1-\beta_{j,k-1}}{1-\beta_{j,k}}\right)$$
if operator l has coverage requirement β_{ji} in region A_j, $j = 1, 2 \ldots, M$.

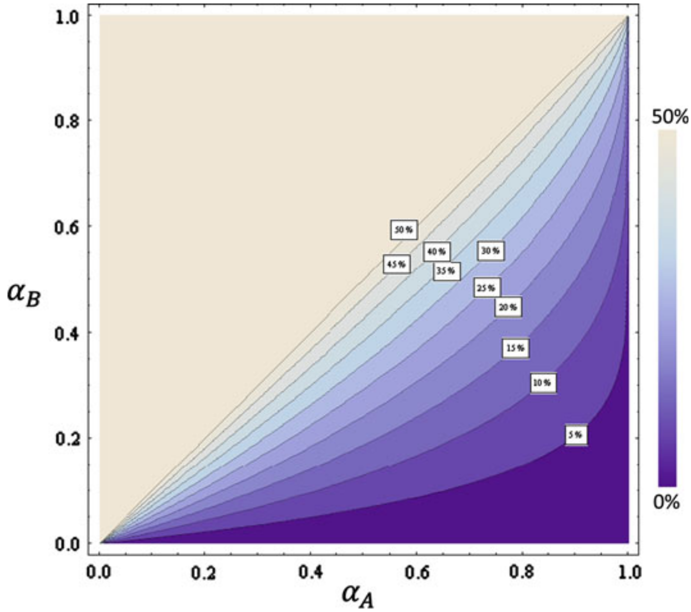

Fig. 12 The percentage of reduced sensors for operator A under cooperation with operator B by using Shapley value, where α is the coverage requirement

Figure 12 shows the percentage of reduced cost for an operator under cooperation with one other operator in one area. In Fig. 12, we see an operator with lower coverage requirement can reduced up to 50 % of cost. The more operators in a coalition, the more reduced percentage one can achieve. We also see that an operator with higher coverage requirement will also cost more than others, which is an result of fair share. In summary, the method of Shapley Value can be extended to other situations with different payoff structure and may serve as a cure for the high cost of machine deployment.

4.4 Coverage of Service of Robots with Mobility

As mobility should be taken into account in M2M for wireless robotics. We use a simple illustration to show the percentage of time for service availability due to coverage within the communication region constituted by the machine swarm. We use the as a system quality of service (QoS). We consider a somewhat simplified but inspiring case. Let a robot moving with an uniform speed v across a field constituted by a large sensor swarm with density λ. The robot crosses the field by following a path L with total length $|L|$. The mean percentage of time of the robots within the coverage region of the sensor swarm is ϕ. And ϕ can be calculated as follows.

$$\phi = \frac{E\left[\int_L 1_{\{\text{x is covered by some sensors}\}} dx\right]/v}{|L|/v} = \frac{\int_L E\left[1_{\{\text{x is covered by some sensors}\}}\right] dx}{|L|}$$

$$
\begin{aligned}
&= \frac{Pr\{\text{x is covered by some sensors}\}|L|}{|L|} \\
&= 1 - e^{-\lambda\pi r^2} = CVF
\end{aligned}
\tag{18}
$$

Thus the percentage of time of coverage by some sensors is exactly equal to the coverage fraction (CVF) of sensor swarm. In fact, this property can be generalized to a family of sensor network described in the following proposition.

Proposition 3 *If the set of sensors and its sensing area can be modeled as a stationary ergodic random closed set* [41] *(e.g. PPP deployment with i.i.d. random compact sensing area), the mean percentage of time for a robot being under coverage of sensors when moving across the sensor swarm with uniform speed is equal to the coverage fraction (CVF) of the sensors.*

Proof Let ϕ be the mean percentage of time then

$$
\begin{aligned}
\phi &= \frac{E\left[\int_L 1_{\{\text{x is covered by some sensors}\}} dx\right]/v}{|L|/v} \\
&= \frac{\int_L E\left[1_{\{\text{x is covered by some sensors}\}}\right] dx}{|L|} \\
&= \frac{Pr\{\text{x is covered by some sensors}\}|L|}{|L|} \text{ (by stationarity)} \\
&= CVF \text{ (by stationarity and ergodicity)}
\end{aligned}
\tag{19}
$$

The example shows that coverage is important for robotics with mobility. In this section, we always assume the swarm can be modeled by Boolean model so the coverage and mean percentage of time under service is equivalent. However, for non-uniform sensor deployment, the Proposition 3 may fail, and the mean percentage of time may not be equivalent to the coverage fraction. We also expect cooperation working for mobility. □

5 Conclusions

The entire information system for wireless robotics involves computation for robot operation and M2M communications for twofold purpose, control of robots and information exchange with environment (primarily information collection from sensors). In Sect. 3, we demonstrate in-network computation to be useful to significantly reduce the number of packets to transmit and thus reduce the required valuable communication bandwidth. Effective communication obviously can also reduce the computation. Along with machine coverage, more in-depth understanding of in-network computation may suggest further research toward optimal design of entire information systems for wireless robotics, to facilitate effective systems.

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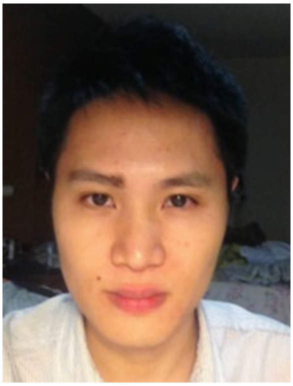

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