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Time-optimized contextual information forwarding in mobile sensor networks

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HIGHLIGHTS

- We study on the scheduling of Context Forwarding (CF) in Mobile Sensor Networks (MSNs).
- We formulate the CF scheduling problem as an optimal stopping time problem.
- We propose an optimal CF policy over MSN.
- The proposed policy exhibits efficient CF in MSN.

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ABSTRACT

We study on the forwarding of quality contextual information in mobile sensor networks (MSNs). Mobile nodes form ad-hoc distributed processing networks that produce accessible and quality-stamped information about the surrounding environment. Due to the dynamic network topology of such networks the context quality indicators seen by the nodes vary over time. A node delays the context forwarding decision until context of better quality is attained. Moreover, nodes have limited resources, thus, they have to balance between energy conservation and quality of context. We propose a time-optimized, distributed decision making model for forwarding context in a MSN based on the theory of optimal stopping. We compare our findings with certain context forwarding schemes found in the literature and pinpoint the advantages of the proposed model.

1. Introduction

1.1. Motivation

A mobile context-aware system (MCAS) is in need of the consumption of quality contextual information (context) [37] disseminated among nodes in a mobile sensor network (MSN). Nodes form ad-hoc distributed processing networks that produce easily accessible and quality-stamped information about the surrounding environment. The objectives for the nodes are to sense, process, and transmit context to other nodes. Since nodes have limited resources, they have to balance between energy conservation and quality of context, while transmitting a quantum information. Nodes are trying to disseminate up-to-date pieces of context, captured by other nodes (sources). Useable stored information is retrieved by a MCAS from the nodes. A MCAS exploits up-to-date disseminated context in order to provide enhanced services such as environmental monitoring, security surveillance, military operations, undersea explorations, contextual and situational inference and reasoning [26,31,3].

We consider a MSN involving (a) source nodes (sources), equipped with sensors that generate (sense) and forward context (e.g., luminance, humidity, temperature), and (b) consumer nodes (consumers), that receive, store, and forward context to their neighbours. The consumers attempt to disseminate context of high quality as much as possible while being energy efficient; i.e., keeping the communication load in low levels. This motivated us to introduce an optimally scheduled, quality-aware context forwarding model for the consumers. The proposed model schedules the context forwarding decision (CFD) within a finite time horizon by reducing data transmission and overhead (possible context replication) in light of context quality.

Context quality refers to the utility entailed to a MCAS by the consumption and use of the circulated context in the MSN. We establish context quality through an ageing framework which deprecates context, thus, leading from high to low quality. Freshness is a typical indicator of the quality of context. Consider two pieces of context p and q and a relation $p \succ q$, which denotes that p is *better* than q. The interpretation of the relation $\succ$ associates with the quality indicator of context [27]. Specifically, better context p can be for instance, 'more fresh'; i.e., more up-to-date sensed values, or 'more reliable'; i.e., sensed values captured by reliable/trustworthy

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sources, or 'more specific'; i.e., more detailed[1] context [2], than q referring to the perspective of interest of the MCAS [8]. Each node compares received p with the locally stored q. If $p \succ q$ then the node accepts p, otherwise, the node does not replace q with p. Each node can, further, locally refine information independently of other nodes. It is also possible for a node to exploit the received p in order to generate more valuable information and, thus, forward it across the MSN [8]. We assume:

- a MSN, which consists of mobile nodes (sources and consumers). All nodes adopt the same mobility model;
- consumers receive, store, and forward context to their current neighbours;
- consumers are delay tolerant in the sense that context forwarding can be postponed in search for context with highest quality;
- each consumer assumes a finite time horizon for the CFD;
- the quality of context turns obsolete with time.

A consumer specifies a finite time horizon N in which it makes a decision (CFD) to forward the local context p to its neighbours. **Local context** refers to as the locally stored contextual information in the consumer's cache. The consumer should forward p before the horizon N is reached taking into consideration the rate at which p turns obsolete. The context p at time t has a certain quality value, say f_t. The f_t function has certain characteristics to be discussed in subsequent sections. The consumer, at time t, can forward p immediately to its neighbours. However, the consumer could refrain from forwarding p instantly to its neighbours in order to receive better context q than p, possibly, from another consumer or source from its neighbours at a later time. The consumer could also continue receiving pieces of context of possibly *better* f values until the horizon N. It is uncertain whether better context will be received within N. The horizon N relates to the tolerance capability of the consumer to forward context of best quality. A high N value might result to reception of better context but, also, might result to forwarding of nearly obsolete context since no better context was attained. The consumer delays the CFD through the reception of context with as high quality value as possible (relative to those values seen previously) and, then, forwards it to its neighbours. We formulate this *scheduling problem* using optimal stopping theory [30] and analyse the problem using backward induction [10] since the finite horizon constraint cannot be neglected.

1.2. Motivating examples

Quality-aware CFD results to exchange of high quality pieces of context, since consumers delay context forwarding in light of receiving context of high quality. A time-optimized CFD mechanism can enhance the forwarding policy of an autonomous mobile node (e.g., robot). Specifically, many research efforts have studied systems emphasizing in autonomous mobile nodes [9] for supporting distributed intelligence in MSN. The higher quality pieces of context a MCAS receives, the more capable becomes of interpreting and inferring (new) knowledge (e.g., from typical sensor data fusion to reasoning about more specific context/situational awareness [3]). Certain MCASs based on the exchanged context in a MSN are: 'covering' (explore enemy terrain), 'self-assembling' (reconfigurable robots) [1], 'localization' and 'coverage' (improvement of positioning accuracy; location of land mines) [15]. We can distinguish motivating scenarios in which multiple airborne nodes (unmanned aerial vehicles—UAVs) identify as much quality information regarding a phenomenon as possible, thus, enriching their knowledge on the surroundings, and hover in formation over a ground target. Ground nodes (unmanned ground vehicles—UGVs) collect spatial disseminated information of high accuracy (high spatial resolution) for applying obstacle-avoidance and formation algorithms to navigate an entire flock of robots to the goal. Furthermore, UGVs enter a building, collect specific up-to-date/fresh contextual information and send back high quality visual images of the interior.

Quality-aware CFD can enhance the context discovery process in [4]. In context discovery [4], consumers collaboratively explore, locate, and track sources that generate context. All consumers cooperatively pursue the acquisition of context of high quality by locating sources in a MSN. Evidently, consumers improve the quality of the discovered context through time-optimized CFD, thus, being capable of providing high quality information for the exploration area leading to reliable real-time inferred situations. In addition, quality-aware CFD can be adopted for keeping the communication load in MSN in low levels. For instance, a consumer can delay in delivering aggregated information to a MCAS in light of accumulating more pieces of information from neighbouring nodes. The more information is aggregated the more data accuracy is achieved (e.g., maximum/average value estimation in a data stream). Evidently, aggregation operation eliminates data redundancy and, thus, communication load. In this case, optimality in CFD copes with the trade-off between energy and delay in data aggregation.

Socially-aware networking (SAN) is an emerging paradigm to solve problems of networks consisting of mobile nodes with social properties, e.g. social relationship and mobility patterns. These characteristics can be utilized to design efficient data forwarding/routing protocols in a mobile social network (MSoN). Specifically, a MSoN is a special kind of delay-tolerant network (DTN) in which mobile users move around and communicate/share data with each other via their carried short-range communication devices. Mobile users with common interests autonomously form a *community*, in which the frequently visited location is their common *home*. MSoC can be a mobile vehicular network, a MSN, and a Pocket Switch Network [38]. Recently, certain socially-aware routing algorithms based on SAN have been proposed, e.g., [21,16,40]. For instance, the idea behind the algorithm in [40] is the opportunistic routing of messages in a MSoN through an optimal set of relay nodes for each home, i.e., each home only forwards its message to the node through its optimal set of relay nodes and ignores other relay nodes. In that sense, the discussed algorithm solves the problem of whether a home should select a visited node as the relay node of message delivery or ignore this visited node to wait for those better relay nodes. Quality-aware CFD can be appropriately adopted in SAN especially when dealing with quality-stamped data sharing being optimally routed within a MSoN home.

1.3. Related work

Methods derived from the optimal stopping theory have been applied to information dissemination in ad-hoc networks. The authors in [43] propose an opportunistic scheduling scheme for ad-hoc communications based on the maximal 'rate of return' problem [32]. The model in [43] treats opportunistic scheduling in ad-hoc networks, in which links cooperate to maximize the overall network throughput. The model in [43] focuses on the level of channel probing, whilst our model focuses on the level of forwarding quality context to neighbouring nodes. The data delivery mechanisms in [5,6] deal with the delivery of quality information to context-aware applications in static and mobile ad-hoc networks, respectively, assuming epidemic-based information dissemination schemes. The mechanism in [5] is based on the probabilistic nature of the 'secretary problem' [33] and the optimal online time series

[1] If the MCAS can infer/deduce context q from context p, then context q can be replaced with context p.

search problem. The work in [6] investigates the optimal scheduling of information delivery in mobile ad-hoc networks. Therefore, the works in [5,6] are not similar to the case studied here. Our study focuses on the forwarding decision of univariate context in MSNs and not on the delivery of context to applications over epidemic-based information dissemination schemes. Moreover, our model highly influences the dynamics of the disseminated information in a MSN.

Significant research in DTNs focuses on minimizing the latency of data delivery. The model in [11] deals with optimal message routing over certain mobility patterns. The model in [41] attempts to minimize latency in data forwarding for real-time mobile target tracking problems. Moreover, the model in [14] copes with the delivery delay of sensed data packets in Vehicular Sensor Networks (VSNs). The discussed model focuses on optimal data packets routing with minimum delay in a VSN making use of (a) vehicle traffic statistics, (b) any-cast routing and (c) trajectory pattern mining of vehicles. In addition, the model in [23] refers to a query-driven data forwarding scheme for delay-sensitive WSNs. The discussed model solves the problems of void paths and isolated nodes that are essential factors influencing the real-time performance of delay-sensitive WSNs. Finally, the swarm intelligence scheme in [24] exploits mobiles nodes' perceiving and learning capability to gather information of density and social tie during communication in MSoNs. Such scheme identifies MSoN communities based on nodes' interests and distinguishes data forwarding into situations of inter-community and intra-community. The discussed scheme performs efficient message scheduling in terms of average latency and message delivery ratio. The proposed quality-aware CFD can be exploited by the abovementioned data delivery and forwarding schemes given that the circulation of high quality pieces of data in a MSN is required.

The authors in [25] proposed a probabilistic forwarding protocol in a delay-tolerant network based on the finite horizon 'asset-selling' problem [28]. Through such a model, one can maximize the 'delivery probability' based on the knowledge about node mobility and mean inter-meeting times between nodes. However, the model in [25] requires a training phase for learning the mobility patterns of nodes and the mean inter-meeting time distribution among nodes. Therefore, our scheme does not require any training phase. In addition, our scheme assumes zero knowledge on the identities of the sources and consumers, the mobility pattern of nodes, and the type and volume of the contextual parameters sensed by each source. Moreover, it should be stressed that the idea behind our model is that it takes into account the quality indicator of circulated data in order to proceed with a CFD; this is not addressed in [25]. Even in the case, in which a consumer is able to learn the mobility behaviour of their encountered nodes, this has no impact on the proposed methodology for CFD. That is because, our model focuses on the received quality values at a consumer end, and is 'blind' to mobility patterns of the consumers in the MSN. Finally, the authors in [13] proposed a mechanism for adaptive optimal time horizon for acknowledgements at the receiving node in delay-tolerant networks. However, the empirical mechanism in [13] is based on experiments and does not guarantee optimality. In our model, the consumers decrease the transmission of redundant and possibly replicated contextual information in a MSN through a time-optimized, quality-aware information forwarding model.

1.4. Contribution & organization

The contributions of this paper include:

- a study on the scheduling problem of the CFD for consumers in a MSN w.r.t. an ageing framework of context quality;
- the derivation of the optimal stopping rule for the discussed problem;
- an optimal univariate context forwarding policy (CFP), through which we obtain high quality of context with significant reduction of the network load.

The paper is organized as follows. In Section 2 we report on context representation and quality, and describe the model dynamics. Section 3 formulates the problem as an optimal stopping time problem, while in Section 4 we propose the optimal CFP. Section 5 reports on the performance evaluation of the proposed model and on the comparative assessment with the models in [8,22], and the Flooding scheme. Section 6 provides a discussion in the case where consumers locally store multiple pieces of context, thus dealing with multivariate CFP. Finally, Section 7 concludes the paper with a discussion on the on-going research agenda.

2. Rationale & preliminary

2.1. Context representation & quality

In this section we model the contextual information circulated in a MSN. We consider a discrete time domain $\mathbb{T} = \{0, 1, \ldots\}$. The set $Y = \{y^1, y^2, \ldots, y^{|Y|}\}$ consists of types of contextual parameters; $|Y|$ is the cardinality of the set Y. A parameter $y \in Y$ represents an environmental parameter, e.g., y^1 is temperature, y^2 is sound, y^3 is humidity, or inferred context/situation like y^4 is 'fire event in a certain area', y^5 is 'an entity accesses forbidden area'. The parameter $y \in Y$ at time $t (t \in \mathbb{T})$ takes a value $v_t \in \mathbb{D}$. The domain $\mathbb{D}$ relates to the parameter, e.g., $\mathbb{D} \subseteq \mathbb{R}$ for environmental parameter. We say that y is *instantiated* at time t with v_t. We define a piece of context p as the tuple:

$$p = \langle y, v, f \rangle \tag{1}$$

where $y \in Y$, $v \in \mathbb{D}$, and f is the quality value of the v value. The f value can refer to temporal validity, freshness, and confidence on a measurement [42]. In this paper, we assume that $f = f_t$ depends on the time t at which the y parameter is instantiated with value v_t. The f_t value represents the freshness of the v_t value and $f_t \in [0, 1]$. $f_t = 1$ indicates that v_t is of maximum quality. $f_t = 0$ indicates that the v_t value is unusable for the node.

Formally, we adopt a function $f : \mathbb{T} \to [0, 1]$ with the following characteristics:

- f is non-increasing in $\mathbb{T}$;
- $f_0 = 1$, where $t = 0$ is the instantiation time for y with v_0;
- $f_\zeta = 0$, for $t \geq \zeta$, with $\zeta > 0$.

The value of $\zeta > 0$ represents a (finite) time interval and depends on the sensed context (variability). For example, for ambient temperature, ζ assumes high values while, for wind speed, ζ is treated conversely. ζ can also derive from context attributes like the Hurst exponent [7]. In this paper, we adopt the linear form $f_t = 1 - \frac{1}{\zeta}t$. At time $t + 1$, $f_{t+1} = f_t - \frac{1}{\zeta}$ and, in general, we have,

$$f_t = \begin{cases} f_{t-1} - \dfrac{1}{\zeta}, & 1 \leq t < \zeta \\ 0, & t \geq \zeta. \end{cases} \tag{2}$$

A piece of context p at time t is called useable if $f_t > 0$; otherwise p is considered as unusable (obsolete). Fig. 1 shows the adopted quality function f. Alternative quality functions can be the rectangular or inverse exponential functions. In Eq. (2), the (obsolescence) rate at which context turns unusable with time t is $\frac{df_t}{dt} = -\frac{1}{\zeta} < 0$. Hence, the interpretation of the relation $\succ$ refers to the freshness

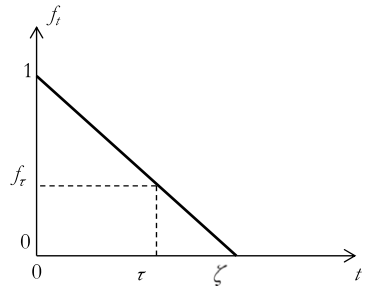

Fig. 1. A linear quality function f_t for context with quality interval ζ.

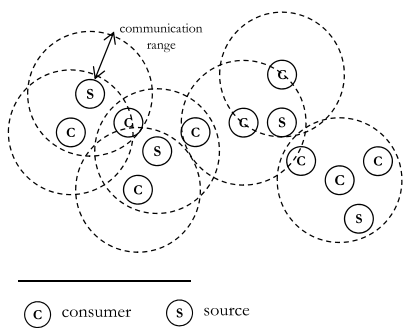

Fig. 2. The MSN model of consumers and sources.

of context p. Specifically, context p (of type y) is *better* than context q of the same type at time t as follows:

$$p \succ_t q \Leftrightarrow f_t^p > f_t^q$$

i.e., the sensed value corresponding to p is more up-to-date than that of q.

2.2. Model dynamics

We model a MSN by an undirected graph $G = (V, E)$, where $V = V^C \cup V^S$ consists of the set of consumers (V^C) and sources (V^S). There is an edge $\{i, j\} \in E$[2] at time t if and only if $i \in V$ and $j \in V$ can mutually receive each other's transmission (this implies that all the links between the nodes are bidirectional). In this case, nodes i and j are neighbours at time t. The set of the neighbours of a node $i \in V$ at t is denoted by $V_t^i = \{j \in V : \{i, j\} \in E\}$. A source s senses and forwards always context p_s with the highest f value, i.e., $p_s = \langle \cdot, \cdot, 1 \rangle$. A consumer c forwards only useable context $p_c = \langle \cdot, \cdot, f_t \rangle$ to its neighbours at time t with $f_t \in (0, 1]$. Unusable copies of pieces of context are not forwarded by any consumer. Different copies are forwarded independently without any knowledge of the status of the other copies. Fig. 2 depicts a MSN (snapshot) of consumer and sources. Each node broadcasts messages only to its neighbours within a communication range; one-hop communication.

The main objective is the forwarding of local context p with the highest possible f value in the MSN. A consumer i has to make a CFD, i.e., forward the local context p_i at some time t, within time horizon N, $1 \le t \le N$ and $N \ge 1$. At each time instance τ, $1 \le \tau \le t$, the consumer

- receives a piece of context p_j from each neighbour $j \in V_\tau^i$ and,
- replaces p_i with p_j, if $p_j \succ p_i$.

[2] Due to mobility, the set E can change over time.

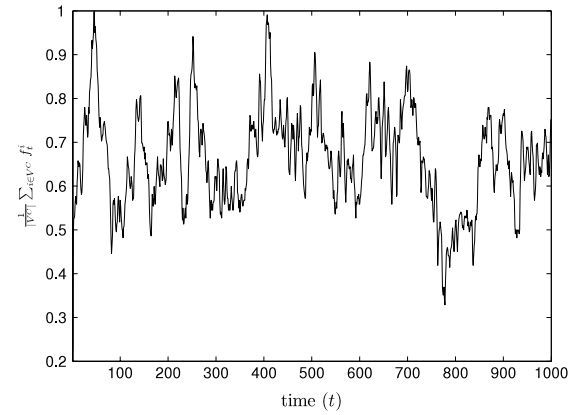

Fig. 3. The mean quality value $\frac{1}{|V^C|}\sum_{i\in V^C}(f_t^i)$ corresponding to the forwarded pieces of context by the consumers, if they deterministically forward context at each time t.

A 'waiting' cost is induced to the consumer i for each time instance τ until forwarding p_i. This cost is associated with the rate $-\frac{1}{\zeta}$. The problem is to determine how many time instances the consumer will passby until receiving better context than the local context and, then, forward it to the MSN with the constraints that (a) the consumer can wait no more than N and (b) the f decreases over time. Moreover, the consumer i starts a new CFP right after the p_i forwarding.

Consider a consumer i with context $p_i = \langle y, v_t^i, f_t^i \rangle$ at time t and its neighbours V_t^i. If, at time $t + 1$, the consumer receives from its neighbours the pieces of context $p_j, j \in V_{t+1}^i$, then it considers the context with the maximum f_{t+1}^j value taking also into consideration its local context with quality value f_{t+1}^i decreased by $\frac{1}{\zeta}$, i.e.,

$$f_{t+1}^i = \max\left(f_t^i - \frac{1}{\zeta}, 0\right). \tag{3}$$

Hence, the consumer i at time $t + 1$ replaces its local context p_i based on the following 'context replace' rule:

$$p_i \leftarrow \arg\max\left(\{f_{t+1}^j\}_{j\in V_{t+1}^i} f_{t+1}^i\right). \tag{4}$$

If, for some $j \in V_{t+1}^i$, the p_j is obsolete then node j does not forward p_j to consumer i. In addition, regardless of the fact that $V_t^i = \emptyset$ or $V_t^i \neq \emptyset$, at time $t + 1$, the quality f_{t+1}^i of the local context p_i is updated w.r.t. Eq. (3). If at some time t the context p_i turns unusable (i.e., $f_t^i = 0$) then the consumer has the *null* context notated by $p_\perp$. It is worth noting that $p_\perp$ is never forwarded, even horizon N reaches at end.

Fig. 3 depicts the dynamic nature of the quality of the circulated pieces of context in a MSN. One can observe the mean quality value of all pieces of context that are deterministically forwarded by each consumer at time t; i.e., each consumer forwards its local context at each time t. Nonetheless, a consumer could wait before forwarding its local context in light of receiving context of better quality. This policy can enhance the quality of the disseminated context in the MSN. Specifically, the consumer should define an optimal CFP in order to maximize the expected quality of the disseminated context within N time horizon. Through such policy, the consumer avoids flooding the MSN with pieces of context constantly and attempts to disseminate context with the highest quality.

2.3. Optimal stopping theory

The theory of optimal stopping [30,34] is about the problem of choosing the best time to take a given action based on sequentially

observed random variables in order to maximize an expected payoff. The optimal stopping problem is defined by a sequence of random variables $X_1, X_2, \ldots$ whose joint distribution is known and a sequence of real-valued payoff functions $J_0, J_1(x_1), J_2(x_1, x_2), \ldots$. Let $(\Omega, \mathcal{B}, \mathcal{P})$ be the probability space, and $\mathcal{F}_t$ be the sub-σ-field of $\mathcal{B}$ generated by $X_1, \ldots, X_t$. We have a sequence of σ-fields as $\mathcal{F}_0 \subset \mathcal{F}_1 \subset \cdots \subset \mathcal{F}_t \subset \cdots \subset \mathcal{B}$. A stopping time is defined as a random variable $T \in \{0, 1, \ldots, \infty\}$ such that the event $\{T = t\}$ is in $\mathcal{F}_t$. Our goal is to choose an optimal stopping time t^* to maximize the expected payoff $\mathbb{E}\{J_{t^*}\}$. If there is no bound on the number of stages at which one has to stop, this is an infinite horizon problem and the optimal return can be computed via the optimality equation. When there is a known upper bound on the number of stages, it is a finite horizon problem and the optimal return can be solved by backward induction [10]. Representative optimal stopping time problems are the 'asset-selling problem' [28], the 'secretary problem' [33], the 'odds-algorithm' [36], and the 'maximizing the rate of return' [20]. Details on this topic can be found in [20].

3. Problem formulation

In this section we formulate the discussed scheduling problem as an optimal stopping time problem. Let $t_{CURRENT} \in \mathbb{T}$ be the current absolute discrete time. The consumer attempts to forward as fresh context as possible in the interval $[t_{START}, t_{START} + N]$; $t_{START} \in \mathbb{T}$. We use below the time index t defined as $t = t_{CURRENT} - t_{START}$ and, thus, $1 \le t \le N$. Without loss of generality, the decision time horizon N is the same for all consumers, since the CFP is independently adopted by each consumer. We assume that the consumer follows the context update and replace rules in Eqs. (3) and (4), respectively. The consumer could immediately forward context to its neighbours at $t = 1$, thus, no delay would have been experienced. This means that the consumer floods the MSN with the available context. However, the consumer can delay its CFD in order to receive possibly better context than the local context. As the consumer moves around, it communicates with neighbouring consumers and/or sources. Yet, the delay of the consumer in the CFD making may render the locally stored context obsolete. But, on the other hand, there might be a high likelihood of receiving pieces of context of better quality.

At each time instance t, the consumer i first updates the quality of p_i using Eq. (3) and then considers the maximum quality value f_t^* of the received pieces of context from its neighbours V_t^i including its local context, i.e.,

$$f_t^* = \max\left(f_t^1, f_t^2, \ldots, f_t^{|V_t^i|}, f_t^i\right) \tag{5}$$

where $|V_t^i|$ is the number of neighbours of consumer i. The consumer i (at time t) replaces its local context p_i using Eq. (4) and, thus, it

- either forwards p_i to its neighbours with quality f_t^*, or
- continues the CFP to the next time instance $t + 1$.

Hence, the consumer deals with the finite horizon optimal stopping problem with 'waiting' cost as follows:

$$J(f) = \sup_{1 \le t \le N} \mathbb{E}\left\{f - \frac{1}{\zeta}t\right\} \tag{6}$$

where quality $f \in [0, 1]$ and the supremum is taken over all (stopping) times t. $J(f)$ is the maximum expected payoff obtained by the proposed optimal stopping rule (defined below). The consumer i forwards p_i with quality f_t^* at t, at which the supremum in Eq. (6) is attained. In our case we obtain the σ-fields

$$\mathcal{F}_t = \{f_1^*; f_2^*; \ldots; f_t^*\}.$$

If $t = N$ then the consumer i should forward p_i to its neighbours provided that p_i is useable. The problem is to find an *optimal stopping time* t^* for context forwarding, which maximizes the expected payoff $\mathbb{E}\{f^* - \frac{1}{\zeta}t^*\}$. That is, the consumer makes a decision on whether or not to forward local context (stop the CFP) based on $\mathcal{F}_t$ in order to maximize the expected payoff.

4. Optimal context forwarding policy

In this section, we propose a CFP which results to an optimal stopping rule for the problem in Eq. (6). Let z_t be the quality value seen by the consumer i. Since consumer i takes a CFD with respect to the quality value, we refer that consumer i is at *state* z_t at time t. Let also $z_\top$ be the terminating state for the CFD process. Hence, based on this notation, we obtain that:

- a state $z_t = z_\top$ at $t \le N$ indicates that the consumer forwards p_i with f_t^* quality value.
- a state $z_t \ne z_\top$ at t indicates that the consumer has not yet forwarded p_i. In such case, the state z_t refers to the quality value of the previous time $t - 1$, i.e.,

  $$z_t = f_{t-1}^*.$$

In addition, we consider the fictitious state $z_1 = 0$. The decision at time t, d_t, takes two values: D_1 = 'stop and forward context' and D_2 = 'continue and do not forward context'. Hence, the system equation of the consumer is:

$$z_{t+1} = \begin{cases} z_\top & \text{if } z_t = z_\top \text{ or } (z_t \ne z_\top \text{ and } d_t = D_1) \\ f_t^* & \text{otherwise; } d_t = D_2. \end{cases} \tag{7}$$

At each time t, the quality value of the local context decreases by $\frac{1}{\zeta}$. $J_t(z_t)$ denotes the optimal payoff value function if the consumer is at state z_t (i.e., quality value) and takes the decision d_t. Then, for the Nth time, we obtain:

$$J_N(z_N) = \begin{cases} z_N - \dfrac{1}{\zeta}N & \text{if } z_N \ne z_\top \\ 0 & \text{if } z_N = z_\top \end{cases} \tag{8}$$

and for time $t = 1, \ldots, N - 1$

$$J_t(z_t) = \max\left(z_t - \frac{1}{\zeta}t, \mathbb{E}\{J_{t+1}(f_t^*)\}\right) \tag{9}$$

with

$$z_{t+1} = f_t^*.$$

A continuously high quality value f_t^* as $t \to N$ indicates that the consumer is more confident on forwarding p_i to its neighbours. On the other hand, the cumulative decrease in the quality value prompts the consumer not to 'delay' its CFD, since it has to make a decision within N.

The $\mathbb{E}\{J_{t+1}(f_t^*)\}$ denotes the expected payoff if the consumer continues the CFD process and receives the pieces of context from its neighbours at the time instance $t + 1$. Hence,

- it is optimal to stop at state z_t **if** $z_t \ge \mathbb{E}\{J_{t+1}(f_t^*)\} + \frac{1}{\zeta}t$ with $f_t^* = z_{t+1}$;
- **else**, it is optimal to continue.

  If $a_t = \mathbb{E}\{J_{t+1}(f_t^*)\} + \frac{1}{\zeta}t$ then

$$J_t(z_t) = \max\left(z_t - \frac{1}{\zeta}t, a_t - \frac{1}{\zeta}t\right) = \max(z_t, a_t) - \frac{1}{\zeta}t.$$

This indicates that the optimal choice, when the consumer evaluates the $z_t = f_{t-1}^*$, is made according to the following *optimal stopping rule*:

$$\begin{cases} \text{forward context with } z_t \text{ quality, if } z_t > a_t \\ \text{continue and do not forward context, if } z_t < a_t. \end{cases} \tag{10}$$

If $z_t = a_t$ then both decisions are optimal. From Eq. (10) it is derived that the optimal CFP is determined by the sequence of the scalar (decision) values $a_0, a_1, \ldots, a_{N-1}$ through which the consumer decides either to forward context or continue the CFD process.

Lemma 1. *The decision values $a_0, a_1, \ldots, a_{N-1}$ for the consumer are inductively obtained for $t = N - 1$ down to 0 through the following equation*

$$a_t = a_{t+1}P^*(a_{t+1}) + \int_{a_{t+1}}^{1} f\, dP^*(f) - \frac{1}{\zeta}. \tag{11}$$

The terminal condition in the recursive Eq. (11) is

$$a_{N-1} = \mathbb{E}\{f^*\} - \frac{1}{\zeta}$$

and $P^*(f) = Prob(f^* \le f)$ is the cumulative distribution function (CDF) of f^*.

Proof of Lemma 1. We have that $J_t(f^*) = \max(f^*, a_t) - \frac{1}{\zeta}t$. For $t = 0, \ldots, N-1$ we obtain

$$a_t = \mathbb{E}\{J_{t+1}(f^*)\} + \frac{1}{\zeta}t = \mathbb{E}\{\max(f^*, a_{t+1})\} - \frac{1}{\zeta}.$$

For $a_{t+1} \in [0, 1]$ we obtain

$$\begin{aligned} a_t &= \int_0^{a_{t+1}} a_{t+1}\, dP^*(f) + \int_{a_{t+1}}^{1} f\, dP^*(f) - \frac{1}{\zeta} \\ &= a_{t+1}P^*(a_{t+1}) + \int_{a_{t+1}}^{1} f\, dP^*(f) - \frac{1}{\zeta} \end{aligned}$$

and, the terminal condition in the above recursive equation is

$$a_{N-1} = \mathbb{E}_{f^*}\{J_N(f^*)\} + \frac{1}{\zeta}(N-1) = \mathbb{E}\{f^*\} - \frac{1}{\zeta}. \quad \square$$

Lemma 2. *For the decision values a_t it holds that $a_t \ge a_{t+1}$, that is, the consumer relaxes its CFD as $t \to N$.*

Proof of Lemma 2. Note that from $J_t(f^*) = \max(f^*, a_t) - \frac{1}{\zeta}t$ we have $J_{N-1}(f^*) \ge J_N(f^*)$ for all $f^* \in [0, 1]$. Now, if $W_t(f^*) = J_t(f^*) + \frac{1}{\zeta}t$, then we obtain $W_t(f^*) = \max(f^*, \mathbb{E}\{W_{t+1}(f^*)\} - \frac{1}{\zeta})$ and, thus, $W_{N-1}(f^*) \ge W_N(f^*)$. Hence, for $t = N-2$ we also have, for all f^*

$$\begin{aligned} W_{N-2}(f^*) &= \max\left(f^*, \mathbb{E}\{W_{N-1}(f^*)\} - \frac{1}{\zeta}\right) \\ &\ge \max\left(f^*, \mathbb{E}\{W_N(f^*)\} - \frac{1}{\zeta}\right) \\ &= W_{N-1}(f^*). \end{aligned}$$

In the same manner, for all $f^* \in [0, 1]$ and t, we see that $W_t(f^*) \ge W_{t+1}(f^*)$ and $J_t(f^*) \ge J_{t+1}(f^*)$. Hence, since

$$a_t = \mathbb{E}\{W_{t+1}(f^*)\} - \frac{1}{\zeta} \ge \mathbb{E}\{W_{t+2}(f^*)\} - \frac{1}{\zeta} = a_{t+1}$$

we obtain $a_t \ge a_{t+1}$, as originally stated. $\square$

The calculation of the $P^*(f)$ has as follows. Consider at time t that the consumer i has $|V_t^i|$ neighbours. Hence, we have that $f_t^* = \max\left(\{f_t^j\}_{j \in V_t^i}, f_t^i\right)$, that is f_t^* is the maximum of the $n_t = |V_t^i| + 1$ i.i.d. variables. If the maximum value is lower than f^*, that means all f_t^k, $k = 1, \ldots, n_t$ are, thus,

$$P^*(f^*) = P(f_t^1 \le f^*, \ldots, f_t^{n_t} \le f^*) = \prod_{k=1}^{n_t} P^{(k)}(f_t^k)$$

where $P^{(k)}(f)$ is the CDF of f^k. We assume that for each time t, consumer i has number of neighbours equals to the mean degree of connectivity, i.e., $\frac{1}{N}\sum_{t=1}^{N}|V_t^i| = \lambda$. Hence, we obtain $n_t = \lambda + 1 = n$; $1 \le t \le N$. Moreover, we assume that the f^k variables are uniformly distributed in [0, 1] with CDF $P^k(f) = f$ and $\mathbb{E}\{f^k\} = \frac{1}{2}$. The knowledge of optimal policies in this case is sufficient to obtain an optimal stopping rule for any continuous $P^*(f)$ as one applies results obtained for the uniform distribution in [0, 1] to the sequence $P^*(f_1^*), P^*(f_2^*), \ldots, P^*(f_N^*)$ [19]. Hence, we obtain that $P^*(f) = \prod_{k=1}^{n} P^{(k)}(f) = (f)^n$ and, by having probability density function $n(f)^{n-1}$, then

$$\mathbb{E}\{f^*\} = \mathbb{E}\{\max(f^1, \ldots, f^n)\} = \frac{n}{n+1}.$$

It is worth noting that, for completeness reasons and make the paper self-contained, we provide, in the Appendix A, an incremental learning method for estimating the $P^*(f)$ and the corresponding $\mathbb{E}\{f^*\}$ on a consumer. From Eq. (11) we obtain the recursive equation for the a_t values for $t = N-1$ down to 0:

$$a_t = \frac{1}{n+1}(a_{t+1}^{n+1} + n) - \frac{1}{\zeta} \tag{12}$$

with $\frac{1}{\zeta} \le \frac{n}{n+1}$ and $a_{N-1} = \frac{n}{n+1} - \frac{1}{\zeta}$. Indeed, for $0 \le a_{N-1} \le 1$ and $0 \le a_{t+1} \le a_t \le 1$ (see Lemma 2) we obtain that $0 \le \mathbb{E}\{f^*\} - \frac{1}{\zeta} \le 1$ or $\frac{1}{\zeta} \le \frac{n}{n+1}$.

Finally, for $t = 0$, we have no previous estimation for the quality value f^*. If the consumer does not wait at all, the payoff is zero. On the other hand, if the consumer waits for the first estimation of f_1^*, the expected payoff will be

$$\int_0^1 J_1(f)\, dP^*(f) = \int_0^1 \max(f, a_1)\, dP^*(f) - \frac{1}{\zeta} = a_0 - \frac{1}{\zeta}.$$

Hence, we obtain a rule which determines the optimal initial choice, as follows:

$$\begin{cases} \text{do not adopt the CFP} & \text{if } a_0 < \dfrac{1}{\zeta} \\ \text{initiate the CFP} & \text{if } a_0 \ge \dfrac{1}{\zeta}. \end{cases}$$

This means that the expected payoff obtained using the proposed optimal stopping rule is $\max(a_0, \frac{1}{\zeta})$. Fig. 4 shows the a_t decision values for $N = 10$ and diverse n, ζ values.[3] The 'area' above the curve defined by the a_t values relates to positive CFD, i.e., decision D_1. The area below this curve relates to negative CFD, i.e., decision D_2. That is, a consumer forwards its local context at time t if $f_t^* \ge a_t$. Otherwise, it waits for the next time instance to make a CFD. Moreover, if the consumer has not forwarded context up to N then it mandatorily forwards context. Note also that $a_t \ge a_{t+1}$ as indicated by Lemma 2.

The proposed mechanism of the CFP is depicted in Fig. 5. The consumer executes the algorithm shown in Fig. 6 for a specific type of contextual parameter. The input to the algorithm is $\frac{1}{\zeta}$, N, and a_t, $1 \le t \le N$. The decision values a_t are calculated once with $O(N)$ time and space using Eq. (12), and stored in the consumer. At each time t, the consumer receives the quality values from its neighbours V_t^i. Once the consumer decides to forward context at some t^* (optimal stopping time; $1 \le t^* \le N$) then it initiates a new CFD process immediately. Moreover, the consumer forwards context with a (variable) frequency of $\frac{1}{t^*} \in [\frac{1}{N}, 1]$.

[3] The $\zeta \to \infty$ indicates always useable context.

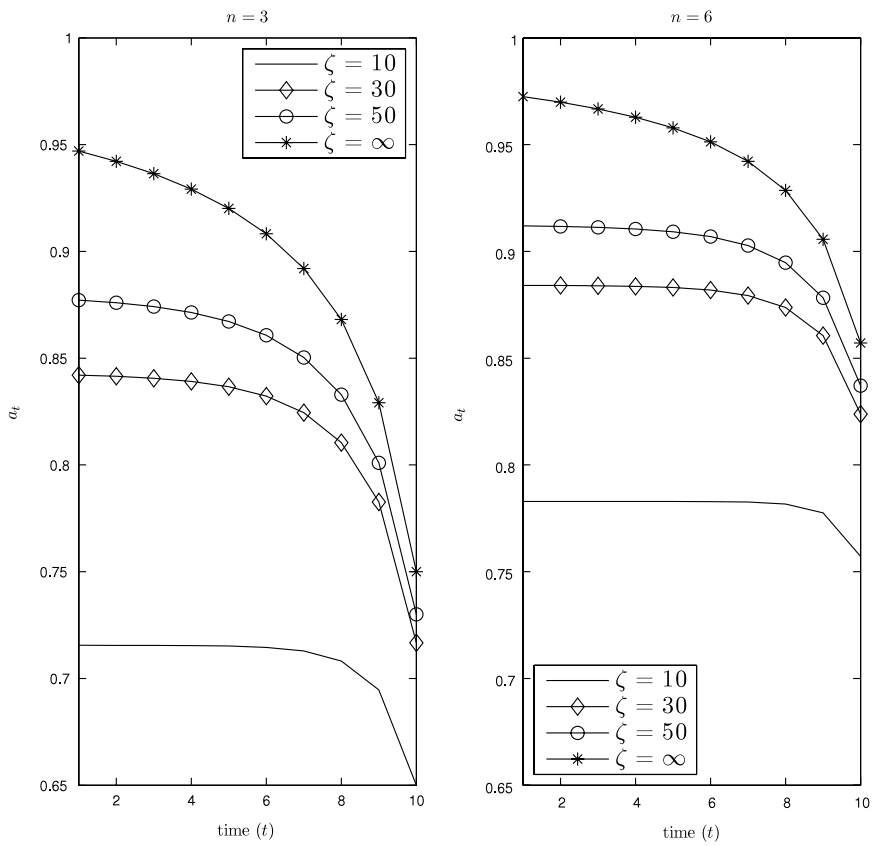

Fig. 4. The a_t decision values for diverse n and ζ values with $N = 10$.

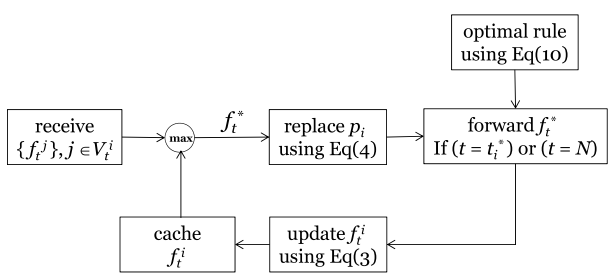

Fig. 5. The context forwarding mechanism for a consumer.

Algorithm Optimal CFP for consumer i
Input: $\zeta, N, \{a_t\}_{t=1}^N$
Begin
$p_i \leftarrow p_\perp$
While$(TRUE)$
  $stopped \leftarrow FALSE$; $t \leftarrow 1$
  While $t \leq N$ **Do**
    update p_i using Eq(3)
    receive $\{f_t^j\}, j \in V_t^i$
    $f^* \leftarrow \max\left(\{f_t^j : j \in V_t^i\}, f_t^i\right)$
    replace p_i using Eq(4)
    If $(f^* \geq a_t)$ **Then**
      forward p_i;
      $stopped \leftarrow TRUE$
      break /*stop*/
    End If
  $t \leftarrow t + 1$
  End While
  If $(f^* = 0)$ **then** $p_i \leftarrow p_\perp$
  If $(stopped = FALSE) \wedge (p_i \neq p_\perp)$ **then forward** p_i
End While
End.

Fig. 6. The consumer algorithm for the optimal CFP.

5. Performance and comparative assessment

The objective of the performance assessment is to verify that the consumer adopting the proposed CFP (a) forwards useable context, (b) demonstrates a robust behaviour when operating with high obsolescence rate values and long decision time horizons, and (c) is less energy consuming in data transmission compared to the models in [8,22] and the Flooding scheme assuming pertinent context quality. Notably, we experiment with diverse values of N depicting the impact of the decision horizon to useable context dissemination.

5.1. Performance metrics

In this section, we report on certain performance metrics for the performance and comparison assessment. Let I_t^i be the indicator function, which indicates whether a consumer $i \in V^C$ forwards context p_i at t, i.e., the optimal stopping time $t_i^* = t$ or the consumer i reaches at the end of time horizon N and has not yet forwarded p_i, as follows:

$$I_t^i = \begin{cases} 1 & \text{if } (t = t_i^*) \text{ or } (t = N), \\ 0 & \text{otherwise.} \end{cases}$$

The $V_t^F = \{i \in V^C : I_t^i = 1\}$ is the set of consumers that makes the decision to forward context p_i at time t with $f_t^{*(i)}$. We refer to the average quality value of forwarded pieces of context of all

consumers in V_t^F at t as

$$\bar{f}_t = \frac{1}{|V_t^F|} \sum_{i \in V_t^F} f_t^{*(i)}, \quad |V_t^F| \neq 0.$$

The $\bar{f}_t \in [0, 1]$ metric should assume as high value as possible.

We also consider the network load for context forwarding for each consumer. We denote as

$$m_t = \frac{1}{|V^C|} \sum_{i \in V^C} I_t^i$$

the percentage of consumers that transmits context at time t. That is, $m_t|V^C| = |V_t^F|$ indicates the number of context transmissions at time t. We require that m_t assume a low value, thus, reducing redundant and replicated data transmission. It is of high importance to investigate whether the forwarded context p_i from consumer i at time t were actually useable for some neighbour $j \in V_t^i$, that is, whether it holds true that $p_i \succ p_j$. Let $V_t^U \subseteq V_t^F \subseteq V^C$ be the set of consumers that forwards at least one piece of useable context to their neighbours, i.e.,

$$V_t^U = \{i \in V_t^F : \exists p_j (p_i \succ p_j), j \in V_t^i\}.$$

Hence, we define as *degree of usability* $\mu_t \in [0, 1]$ the percentage of consumers that transmits useable pieces of context at time t, i.e.,

$$\mu_t = \frac{|V_t^U|}{|V_t^F|}, \quad |V_t^F| \neq 0.$$

The μ_t quantifies the capability of a CFP to disseminate useable pieces of context in a MSN. The $\mu_t \in [0, 1]$ and a μ_t value close to unity indicates that the forwarded context is of high usability for the MSN.

We also have to take into account the delay of the CFD making for each consumer in order to achieve dissemination of useable context. We define as average percentage delay δ_t^N of all consumers in V_t^F the delay t_i^* ($1 \leq t_i^* \leq N$) for the forwarding decision of the consumer i, which forwards context at t. That is,

$$\delta_t^N = \frac{1}{|V_t^F|} \sum_{i \in V_t^F} t_i^*, \quad |V_t^F| \neq 0$$

with $\delta_t^N \in [0, 1]$. A high δ_t^N value indicates that a consumer delays its CFD, i.e., $t_i^* \to N$. However, this might result to the forwarding of high quality context. On the other hand, if the disseminated pieces of context that circulate in the MSN are of high quality then the consumer forwards context at an early stage.

We performed several simulations for evaluating the discussed performance metrics. We assume a finite simulation time $\mathcal{T}$ and obtain the corresponding mean values of the above mentioned metrics, i.e., $\bar{f} = \frac{1}{\mathcal{T}} \sum_{t \leq \mathcal{T}} \bar{f}_t$, $m = \frac{1}{\mathcal{T}} \sum_{t \leq \mathcal{T}} m_t$, $\mu = \frac{1}{\mathcal{T}} \sum_{t \leq \mathcal{T}} \mu_t$, and $\delta^N = \frac{1}{\mathcal{T}} \sum_{t \leq \mathcal{T}} \delta_t^N$.

Finally, we define as *forwarding rate* g_i the frequency of the context forwarding decisions that a consumer makes up to $\mathcal{T}$, i.e.,

$$g_i = \frac{1}{\mathcal{T}} \sum_{t \leq \mathcal{T}} I_t^i.$$

A high g_i value denotes that the consumer i does not delay its CFD. A consumer by adopting the proposed CFP delays its CFD for searching better context within a fixed time horizon N. If time horizon N expires and the consumer has not yet forwarded context, then it deterministically forwards context, if the latter is not null. It is worth noting that at each time t the consumer either makes one CFD or not. Hence, $g_i \leq 1, \forall i \in V^C$. The average forwarding rate for all consumers is denoted by $g = \frac{1}{|V^C|} \sum_{i \in V^C} g_i$. We define as efficiency ϵ of a CFP the capability to forward *useable* context with the *best quality* as *soon* as possible, i.e., with high forwarding rate. The proposed CFP has to forward as much useable context as possible up to horizon N. Therefore, if the CFP could achieve the best quality values with a short delay, this would also be of high importance under certain conditions (e.g., the application specifies certain deadlines). We assess a CFP on how to forward context while incurring delay in the CFD. The efficiency metric for a CFP is defined as follows:

$$\epsilon = \omega_f \bar{f} + \omega_\mu \mu + \omega_g g$$

where $\omega_f, \omega_\mu, \omega_g \in [0, 1]$ are weight factors for balancing the quality, usability and forwarded rate of the forwarded context such that $\omega_f + \omega_\mu + \omega_g = 1$. A CFP should assume ϵ value close to unity ($\epsilon \in [0, 1]$) denoting that such policy forwards high quality/useable context with a short delay.

Table 1
Simulation parameters and notation.

Parameter	Notation	Value/range
$\|V^S\|$	Number of sources	{5, 10, 15, 20}
$\|V^C\|$	Number of consumers	$100 - \|V^S\|$
ζ	Quality interval	{10, 20, 30}
N	Decision time horizon	[3, 200]
ρ	Communication range	20 m
$v_{\min}, v_{\max}$	Minimum speed, maximum speed for RWP	2 m/s, 5 m/s
$p_{\min}, p_{\max}$	Minimum pause, maximum pause for RWP	0 s, 5 s

5.2. Simulation set-up

The simulation set-up has as follows: we consider a MSN, which consists of a set of consumer V^C and a set of sources V^S. Each source $i_S \in V^S$ carries a sensor which corresponds to a contextual parameter $y \in Y$. At each time t, each source i_S instantiates the pieces of context from Y with the current contextual values, and propagates them to the local neighbours with $f_t^{i_S} = 1$. A consumer $i \in V^C$ receives disseminated pieces of context from the current neighbours V_t^i (sources and consumers) at time t, updates local context using Eq. (4), and forwards p_i to V_t^i based on the optimal stopping rule in Eq. (10). We performed 1000 simulation runs. Each run involves sequences of horizon N with simulation time $\mathcal{T} = 1000$. At each sequence, each consumer applies the proposed policy. In each run we construct a random MSN of $|V^C| + |V^S| = 100$ nodes with $\nu = \frac{|V^S|}{|V^S|+|V^C|}\% \in \{5, 10, 15, 20\}\%$. All nodes adopt the same mobility model, which is the random waypoint (RWP) [29] with a 500 m × 500 m terrain and communication range $\rho = 20$ m. The simulation parameters are summarized in Table 1.

5.3. Performance assessment

5.3.1. Quality context forwarding

Fig. 7 shows the probability density function $PDF_{\bar{f}^*}$ of the average f^* from all consumers for simulation time $\mathcal{T}$, $N = 10$ and diverse ν% values. The $PDF_{\bar{f}^*}$ density estimate is based on a normal kernel function and evaluated at 100 equally spaced points that cover the range of the f^* values. Evidently, the more sources a MSN has the higher quality of context is circulated. In the remainder we set $\nu = 10\%$. Figs. 8–10 show the $PDF_{\bar{f}^*}$ for diverse ζ values ($N = 10$), the $PDF_{\bar{f}^*}$ for diverse N values ($\zeta = 10$), and the $CDF_{\bar{f}^*}$ for diverse N values ($\zeta = 10$), respectively. It is worth noting the impact of the rate that context turns obsolete $-\frac{1}{\zeta}$ in Fig. 8. The proposed CFP achieves relatively high quality values with mean value close to 0.7 for all rates and $N = 10$. Moreover, in Fig. 9 we observe that the proposed CFP achieves high quality values as the decision time horizon N gets relatively long. This means that the consumers can delay their CFDs in order to wait for more fresh pieces of context.

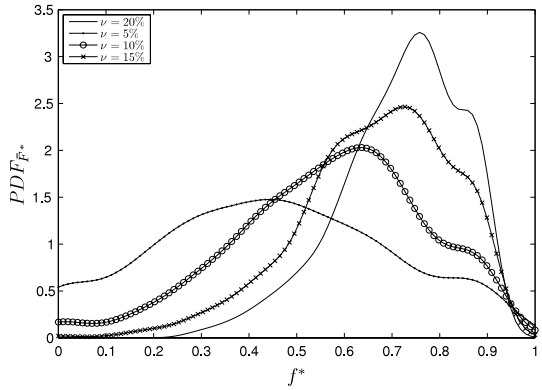

Fig. 7. The $PDF_{\bar{f}^*}$ of all consumers for simulation time $\mathcal{T}$ with $N = 10$ and diverse $\nu\%$ values.

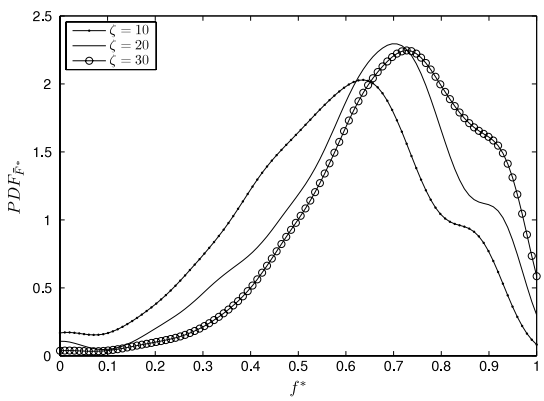

Fig. 8. The $PDF_{\bar{f}^*}$ of all consumers for simulation time $\mathcal{T}$ with $N = 10$ and diverse ζ values.

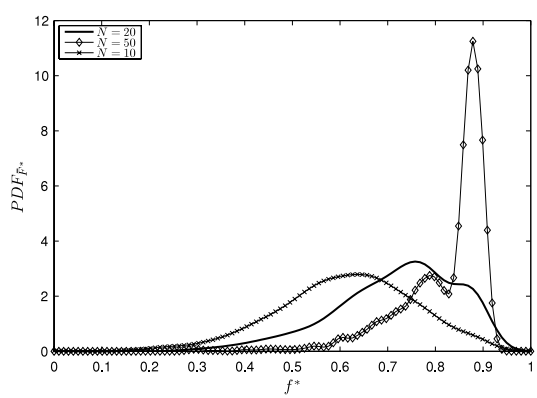

Fig. 9. The $PDF_{\bar{f}^*}$ of all consumers for simulation time $\mathcal{T}$ with $\zeta = 10$ and diverse N values.

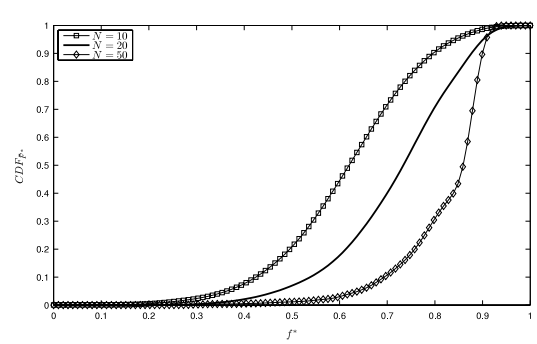

Fig. 10. The $CDF_{\bar{f}^*}$ of all consumers for simulation time $\mathcal{T}$ with $\zeta = 10$ and diverse N values.

Fig. 11 shows the $\bar{f}$ and δ^N vs. $N \in [3, 200]$ for diverse ζ values. Obviously, the longer the horizon N gets the more likely is for a consumer to receive better context. However, it is worth mentioning that as N becomes long then there in no significant improvement on the average quality value of the disseminated context in the MSN; see Fig. 11(left). This is due to the fact that the circulated context turns obsolete with time. Moreover, Fig. 11(right) shows the mean delay in CFD making. We can observe that for $N > 100$ we obtain quite constant delay in the CFD making, i.e., from 12% to ∼16% of the time horizon N, especially for high ζ value. That is, there is no need to prolong the horizon N since the CFDs result to relatively high quality values (over 0.9) and $N > 100$. In the case where ζ is low then the consumers attempt to delay the CFD in high hopes of receiving better context. In addition, the higher the ζ value is, the higher the $\bar{f}$ values are obtained. That is, the consumers are aware of the quality of context and intelligently make CFDs for forwarding high quality context.

5.3.2. Useable context forwarding

Fig. 12 shows the μ and m vs. $N \in [3, 200]$ for diverse ζ values. We obtain useable context as the consumers delay their CFD. This denotes the applicability of the proposed CFP in MSNs where nodes are in need of useable context and avoid reception of unusable information. Specifically, in Fig. 12(left) the proposed CFP achieves high degree of usability especially for long N. It is worth noting that as ζ gets high then μ decreases. This is due to the fact that: a high ζ value (low obsolescence rate) renders consumers to make a CFD at early stages since high quality of context is seen to the consumers; see Fig. 11(left). This, however, comes at the expense of increasing the frequency of the CFDs, thus, the forwarded context (already of high quality) is not so useable to neighbouring consumers, which are more likely to store context of evenly high quality. The high frequency of CFDs, due to high ζ value, is also depicted in Fig. 12(right). Specifically, Fig. 12(right) shows the percentage of consumers that forward context vs. N. For a low ζ value, a low percentage of consumers forward context since they are delaying their CFDs. Moreover, as N gets long, a small number of consumers make a CFD, thus, increasing the lifetime of the MSN, by avoiding redundant context transmission. This can also be observed in Fig. 13. Fig. 13 shows the $|V^F|$ vs. $N \in [3, 200]$ for diverse ζ values. The number of context transmissions decreases with N. That is because, as N gets longer, the consumers are given the opportunity to delay their CFDs, thus, reducing redundant data transmission in light of high quality context forwarding. However, for $N > 100$ the $|V^F|$ assumes a quite constant value since the consumers are urged to forward context due to the obsolescence rate $-\frac{1}{\zeta}$. Moreover, observe that as ζ assumes a high value then we obtain higher $|V^F|$ values comparing with low ζ value. The reason is the same as explained above in the case of the low μ in Fig. 12(left).

5.4. Comparative assessment

We investigate the performance of the proposed model against the *epidemic*-based *Sa*IS model in [8], the spatial Gossip model in [22], and the Flooding scheme.

5.4.1. Models under comparison

The *Sa*IS model [8] exploits the semantic $\succ$ relation for multi-epidemic [17] dissemination in a MSN. In our case, the interpretation of $\succ$ refers to context quality. Hence, in order to adopt the *Sa*IS model in our problem, we have to define the ℓ-level context p^ℓ (epidemic of level ℓ in [8]) as follows:

$$p^\ell = \left\langle y, v, \frac{\ell}{\zeta} \right\rangle, \quad \ell \in [0, \zeta].$$

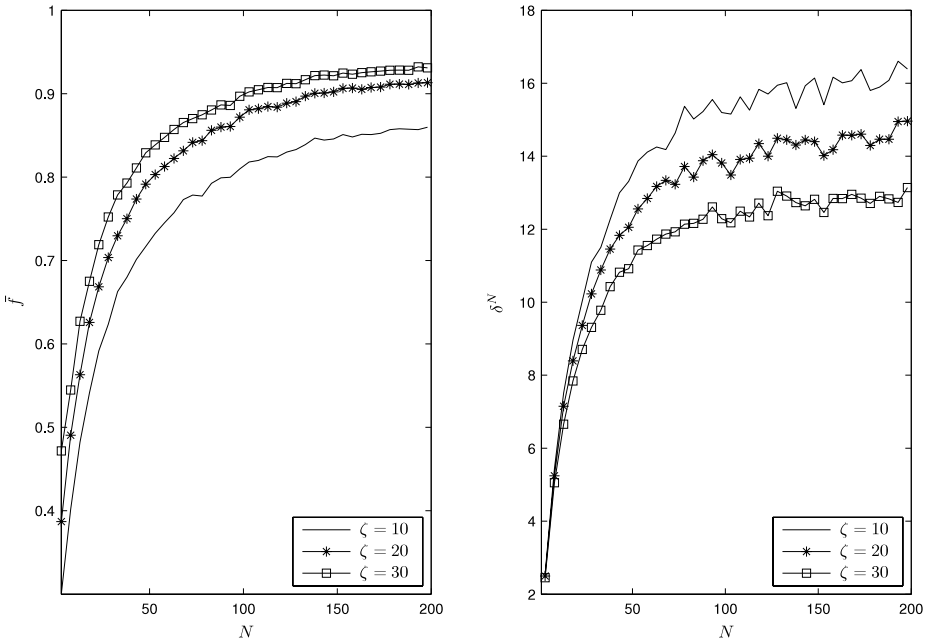

Fig. 11. The (left) $\bar{f}$ and (right) δ^N vs. $N \in [3, 200]$ for diverse ζ values.

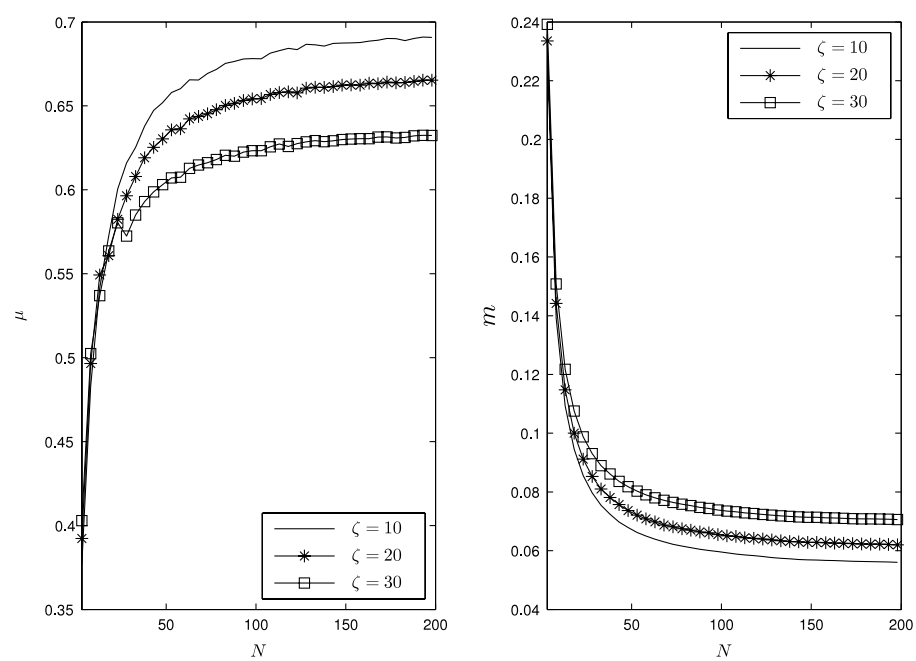

Fig. 12. The (left) μ and (right) m vs. $N \in [3, 200]$ for diverse ζ values.

That is, $p^\ell \succ p^k$ iff $0 \leq k < \ell \leq 1$, which means that a consumer replaces the local context with incoming context of higher quality. The sources forward ζ-level pieces of context. In the S*a*IS model, all nodes disseminate context at time t with constant probability $\beta \in (0, 1]$.

Moreover, we experiment with the Gossip algorithm which falls in the same broader category of information dissemination algorithms. The Gossip algorithm is characterized by its distributed nature and robustness to dynamic network conditions. In a Gossip algorithm, each node picks, according to some underlying (deterministic or random) rule, another neighbour and exchanges information with it. Two basic schemes are discussed in the literature for neighbour selection: the uniform gossip, in which each node chooses to communicate with a randomly chosen node at each step [18], and the standard gossip, in which a node picks, according to a probabilistic distribution, one of its immediate neighbours [12,39]. In addition, the authors in [22] propose the spatial Gossip algorithm, where node selection is based on a probability inversely proportional to the distance between nodes. In our case, the exact knowledge on the entire MSN structure is not known to each node. Instead, each node i (consumer/source) can only locally communicate with its neighbouring nodes (V_t^i) at time t and forward context to them. We compare our model with the local (uniform) Gossip model. In local Gossip, a node i uniformly chooses to forward context to one neighbour $j \in V_t^i$. Finally, in the Flooding scheme, a node i communicates deterministically with all neighbours, that is, at each time t, node i forwards context to its neighbours.

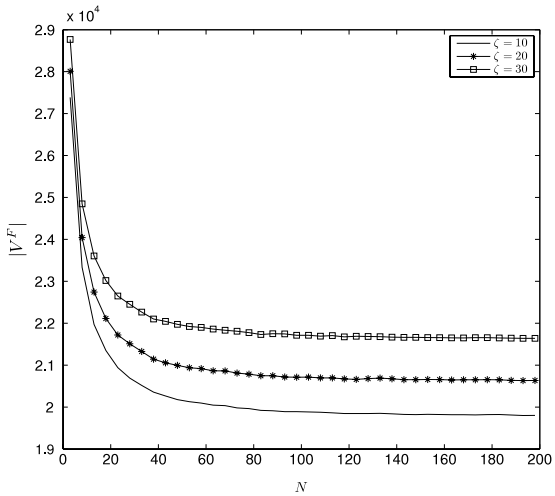

Fig. 13. The $|V^F|$ vs. $N \in [3, 200]$ for diverse ζ values.

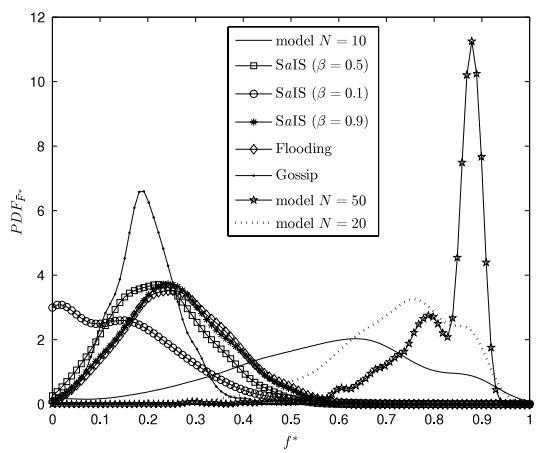

Fig. 14. The $PDF_{\bar{f}*}$ for all models with $\zeta = 10$.

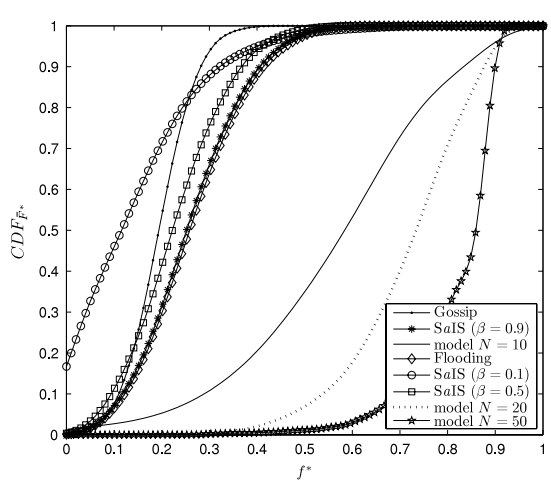

Fig. 15. The $CDF_{\bar{f}*}$ for all models with $\zeta = 10$.

5.4.2. Quality context forwarding

Figs. 14 and 15 show the $PDF_{\bar{f}*}$ and the $CDF_{\bar{f}*}$, respectively, for the Gossip, Flooding, *Sa*IS ($\beta \in \{0.1, 0.5, 0.9\}$) models, and our model ($N \in \{10, 20, 50\}$) with $\zeta = 10$. For all models we assume $\nu = 10\%$.

The proposed CFP (referred to as 'model' in all figures) obtains the highest quality values compared to all models for $N > 10$. We can observe that even for a short delay in CFD making, i.e., $N = 10$, our model achieves better context compared to a scheme that does not delay the CFD. Specifically, in the case of the Flooding scheme, in which there is no delay, we obtain a mean quality of 0.25. This denotes that the consumers flood the MSN most of the time with context of low quality, if not unusable. The *Sa*IS and Gossip models achieve even less quality context w.r.t. our model. Such models stochastically forward context in the MSN in an attempt to decrease redundant data transmission (as will be demonstrated in the remainder). Nevertheless, they defy the fact that local context turns obsolete. Fig. 16 shows the $\bar{f}$ value for all models against N with $\zeta = 10$. For a very low N value ($N = 3$) our model achieves marginally greater $\bar{f}$ compared to the Flooding scheme. For $N = 10$, our model achieves 33% higher context quality than the Flooding scheme. As N gets long, our model significantly outperforms the comparison models in $\bar{f}$ value.

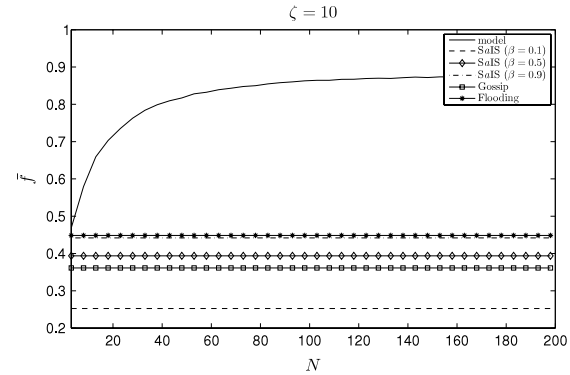

Fig. 16. The $\bar{f}$ vs. N for all models with $\zeta = 10$.

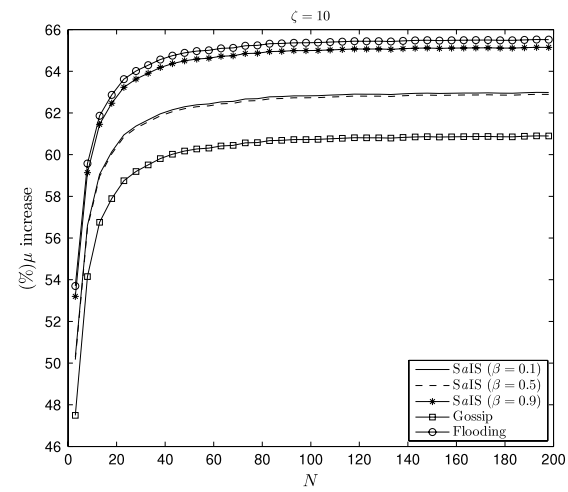

Fig. 17. The percentage increase in μ vs. N for all *comparison* models with respect to our model; $\zeta = 10$.

5.4.3. Useable context forwarding

Fig. 17 shows the percentage increase of the μ metric that our model achieves compared with all models against N and $\zeta = 10$. The proposed CFP is 62% more useable in terms of μ than all comparison models. Even for low N values, our model guarantees dissemination of 47%–54% more useable context in the MSN. This demonstrates the applicability of the proposed CFP to significantly decrease redundant/unusable data transmission in a MSN.

Moreover, we have to compare the network load of the proposed CFP w.r.t. comparison models. Fig. 18 shows the cumulative $\sum_{\tau \le t} |V_\tau^F|$, $1 \le t \le \mathcal{T}$ for all models against t with $\zeta = 10$. We can observe a 80% reduction of the transmitted messages achieved

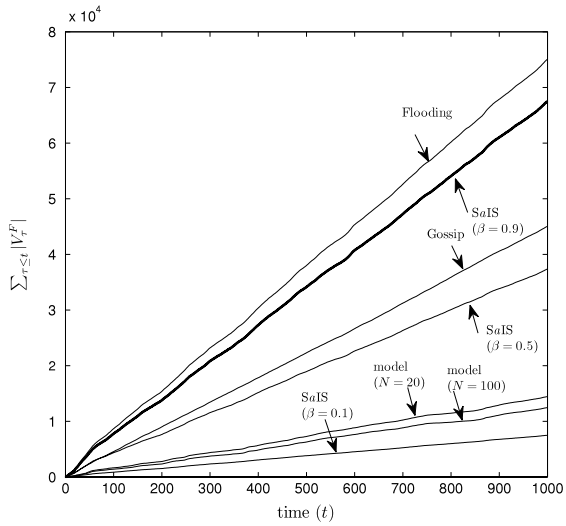

Fig. 18. The cumulative $\sum_{\tau \le t} |V_\tau^F|$, $1 \le t \le \mathcal{T}$ for all models against t with $\zeta = 10$.

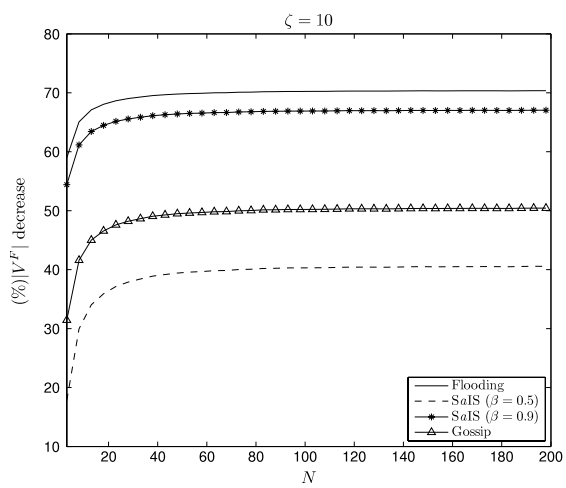

Fig. 19. The percentage decrease in $|V^F|$ vs. N for all *comparison* models with respect to our model; $\zeta = 10$.

by our model compared to the Flooding scheme. In addition, our model forwards 75% more context than the *Sa*IS model ($\beta = 0.1$) but it achieves 240% and 63% higher quality and usability values than the corresponding model. In order to better demonstrate the reduction of data transmission obtain from our model, we examine the percentage decrease of the $|V^F|$ achieved by our model compared with all comparison models. Fig. 19 shows this percentage against N for all comparison models with respect to our model having $\zeta = 10$. We obtain 20%–60% reduction in context transmission for very short horizon N. Evidently, as N increases we obtain higher percentage reduction in data transmission, since our model delays the CFDs. However, this delay has to be taken into consideration in evaluating the efficiency of the models under comparison.

We examine the performance of each model with the capability of forwarding high quality and useable context with high frequency. Fig. 20 shows the distribution of the forwarding rates of all consumers for our model, *Sa*IS, and Gossip. In the Flooding scheme, we obtain $g_i = 1$, since the consumer at each time t deterministically forwards its local context; the forwarding rate for Flooding scheme is not shown in Fig. 20, since it is constant. In the *Sa*IS model, the consumer makes a CFD with rate β, while in the Gossip model, the consumer makes a CFD at time t with probability one assuming that $|V_t^i| > 0$. In our model, the g_i depends on the decision horizon N, the stopping time t_i^*, and the dynamics of the MSN. Evidently, we obtain a low g_i for long horizon N. Moreover, Fig. 21 shows the efficiency ϵ of all models against N with $\zeta = 10$ and $\omega_f = \omega_\mu = \omega_g = \frac{1}{3}$. Overall, we observe that our model demonstrates higher efficiency values than the Gossip and the *Sa*IS model with $\beta \in \{0.1, 0.5\}$. Comparing with the *Sa*IS model having $\beta = 0.9$ and the Flooding scheme, our model is more efficient for $N > 30$ and $N > 40$, respectively. This denotes that the quite deterministic *Sa*IS model ($\beta = 0.9$) and the deterministic Flooding model achieve high forwarding rates, but the corresponding degrees of usability and context quality are low. On the other hand, for $N < 30$, our model increases the forwarding rate, thus, increasing the probability of forwarding relatively low quality context (due to short decision time horizon) or low degree of usability. To sum up, a delay in CFD results in dissemination of high quality context, high useable context, thus, reduction of redundant information. On the other hand, such delay leads to a low forwarding rate. For delay-tolerant consumers in a MSN the proposed CFP demonstrates efficient behaviour in terms of context quality and usability, and energy efficiency.

6. Discussion

In this section we elaborate on a CFP, which proceeds with optimal CFD based on multiple local pieces of context, hereinafter, referred to as Multiple CFP (MCFP). The MCFP is based on M optimal CFPs, running in parallel, corresponding to the top-M local pieces of context in terms of quality. In this case, consumer i (1) stores, at each time instance t, a list of the top-M local pieces of context, (2) updates their corresponding quality values using Eq. (2), (3) re-evaluates this list at the next time instance taking also into account the pieces of context received from its neighbouring nodes. The MCFP is based on M order statistics from the top-M list. Consider that consumer i stores M local pieces of context $(f^1, f^2, \ldots, f^M)$. The order statistics $(f^{(1,M)}, f^{(2,M)}, \ldots, f^{(M,M)})$ are random variables defined by sorting the realizations of $(f^1, f^2, \ldots, f^M)$ in increasing order. For instance, the minimum value of the top-M list is the order statistic $(1, M)$ associated with the variable $f^{(1,M)} = \min\{f^1, f^2, \ldots, f^M\}$, the maximum value of the top-M list is the order statistic (M, M) associated with the variable $f^{(M,M)} = \max\{f^1, f^2, \ldots, f^M\}$, and the (k, M) order statistic, i.e., $f^{(k,M)}$, is the kth smallest value of the top-M list.

Let, at time instance t, consumer i receive $\lambda = |V_t^i|$ pieces of context from its neighbours $f_t^j, j \in V_t^i$ and its local pieces of context correspond to K quality values $f_t^{i1}, f_t^{i2}, \ldots, f_t^{iK}$ after being updated using Eq. (2). Consumer i then deals with M quality values, $M = K + \lambda$, associated with the received pieces of context from its λ neighbours and its K local pieces of context, i.e.,

$$\begin{aligned} f^{(1,M)} &= \min(\{f_t^j\}_{j=1}^{\lambda}, f_t^{i1}, f_t^{i2}, \ldots, f_t^{iK}) \\ f^{(2,M)} &= 2\text{nd}\min(\{f_t^j\}_{j=1}^{\lambda}, f_t^{i1}, f_t^{i2}, \ldots, f_t^{iK}) \\ \cdots &= \cdots \\ f^{(M,M)} &= M\text{th}\min(\{f_t^j\}_{j=1}^{\lambda}, f_t^{i1}, f_t^{i2}, \ldots, f_t^{iK}) \\ &= \max(\{f_t^j\}_{j=1}^{\lambda}, f_t^{i1}, f_t^{i2}, \ldots, f_t^{iK}). \end{aligned}$$

The notation kth $\min(A)$ refers to the kth smallest element of set A. It is worth noting that the (single) CFP stores only the maximum quality value f^* of $(\lambda + 1)$ pieces of context (i.e., only the $(\lambda + 1, \lambda + 1)$ order statistic) while, MCFP stores all order statistics (k, M), $k = 1, \ldots, M$. In the case where $K = 1$, thus, $M = \lambda + 1$, MCFP stores all $(k, \lambda+1)$ order statistics ($k = 1, \ldots, (\lambda+1)$), thus, including also the $(\lambda + 1, \lambda + 1)$ order statistic, corresponding to that of CFP, i.e., $f^{(\lambda+1,\lambda+1)} = f^*$.

The MCFP consists of M parallel optimal CFPs each one corresponding to the (k, M) order statistic, $k = 1, 2, \ldots, M$, such that $\text{CFP}_1, \text{CFP}_2, \ldots$, and CFP_M deal with the minimum quality value,

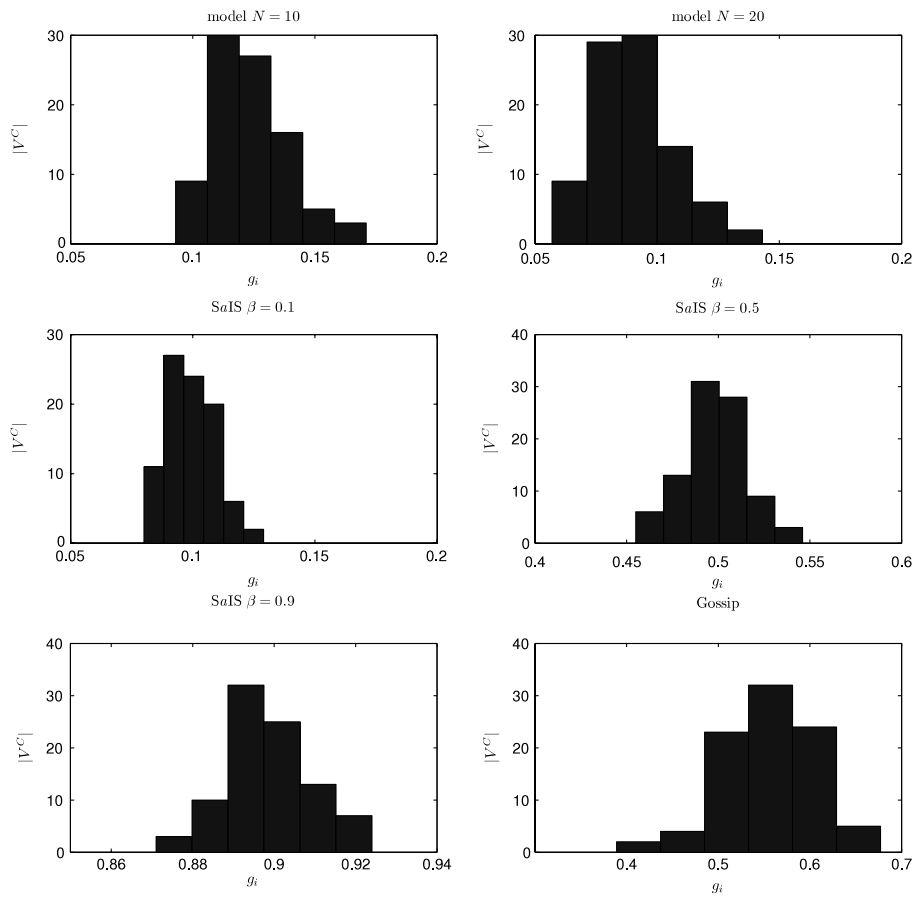

Fig. 20. The distribution of the forwarding rates of the consumers for our model, SaIS, and Gossip models with $\zeta = 10$; in Flooding we obtain $g_i = 1$.

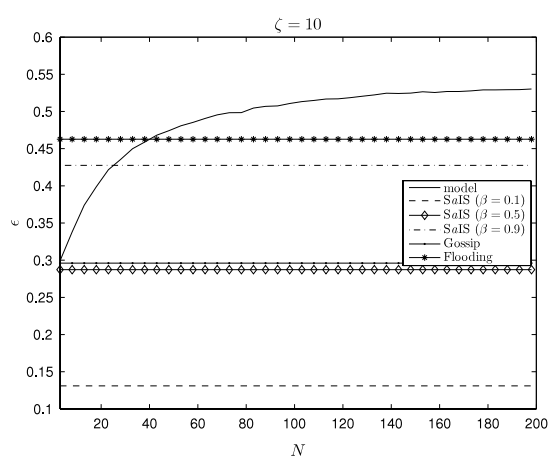

Fig. 21. The efficiency ϵ of all models against N with $\zeta = 10$.

second minimum quality value, ..., and maximum quality value, respectively, out of M quality values. Each CFP$_k$ associates with an optimal context forwarding decision for (k, M) order statistic, CFD$_k$, i.e., it has its own scalar decision values, $a_t^{(k,M)}$, $t = 1, \ldots, N$ (see Lemma 1). Hence, consumer i, at time instance t, makes a CFD$_k$ for forwarding the local piece of context which corresponds to the kth smallest quality value $f^{(k,M)}$, $k = 1, 2, \ldots, M$. That is, in a CFP$_k$ the decision at time t takes two values

- D_1^k = 'stop and forward the kth smallest piece of context of the M stored pieces of context in terms of $f_t^{(k,M)}$,
- D_2^k = 'do not forward the kth smallest piece of context and continue observing $f_{t+1}^{(k,M)}$.

For completeness reasons, Appendix B provides the formulae for scalar decision values $a_t^{(k,M)}$, $t = 1, \ldots, N$, $k = 1, \ldots, M$ corresponding to CFD$_k$.

In MCFP, consumer i needs $O(M) = O(K + \lambda)$ space, while in the single CFP, requires $O(\lambda)$ space. Obviously, in MCFP more pieces of context are circulated/exchanged in the MSN with diverse quality values, since consumers forward also pieces of context which do not correspond to high quality values. Evidently, this decreases the average percentage delay in forwarding context, and increases the frequency of the context forwarding decisions. Specifically, consider the indicator $J_t^{(k,M)} = 1$, when the CFD$_k$ for (k, M) order statistic is D_1^k at time t with probability θ_k; otherwise $J_t^{(k,M)} = 0$ with probability $1 - \theta_k$. If, for simplicity reasons, we assume that $\theta_k = \theta$ for all $k = 1, \ldots, M$, then the expected number of forwarded pieces of context at time t per consumer is $(K + \lambda)\theta$. This denotes that the forwarding rate g_{MCFP} and network load m_{MCFP} for MCFP are K times higher than those attained by the single CFP. In addition, we obtain $O(1/K)$ less delay δ_{MCFP} w.r.t. δ_{CFP}. Since consumers always store and forward the top-M highest quality values, the circulated context in MSN is, on average, of high quality, thus, the consumers forward context at an early stage. Appendix C provides a statistical quantification of the quality of context obtained from MCFP compared to CFP. The idea of storing and optimally forwarding of the top-M pieces of context might be useful for MCAS which is in need of context of moderate quality but cannot tolerate high delays. In such case, MCFP can support time-constrained/low delivery latency MCAS. On the other hand, the single CFP can support delay-tolerant MCAS, which are in need of context of very high context quality. Hence, there is a trade-off between forwarding/circulating quality context and latency in CFD, which can be tuned either by increasing or decreasing K.

7. Conclusions

We study an approach for distributed, optimal scheduling of CFDs in a MSN. We assume that a consumer is delay-tolerant in the sense that context forwarding can be postponed in search for context with highest quality. We treat such scheduling problem as an optimal stopping problem. The constraint of the problem is the specified decision horizon N, in which the consumer has to make a CFD. Moreover, we consider an ageing linear function of the quality of context. We provide a CFP with the corresponding optimal stopping rule. We present a performance assessment and compare our CFP with contextual information dissemination schemes found in the literature. For certain decision time horizons, our model is proved efficient for context dissemination in terms of high context quality and usability while keeping the communication overhead in relatively low levels.

The proposed CFP focuses on univariate context forwarding, that is, all consumers are interested in context of the same type. Moreover, we provide a discussion in the case where a consumer is capable of locally storing multiple pieces of context. Our research agenda deals with the problem of forwarding multivariate context of high quality and usability in a MSN. In this direction, the consumer could perform a parallel realization of the CFPs for each type of context based on a generic quality indicator or, more intelligently, exploit possible correlations (e.g., spatio-temporal relations) among pieces of context of different type in order to make a CFD.

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Appendix A

In this appendix we provide a mechanism, complementary to our model, which can be adopted by a consumer in order to learn the probability density functions of the received context quality values by its encountered consumers. Once such functions are estimated, then the consumer can produce the CDF $P^*(f)$, $\mathbb{E}\{f^*\}$, and, in turn, the scalar decision values $a_0, a_1, \ldots, a_{N-1}$ for making optimal CFDs.

Consider a consumer i, which at time t stores local context with quality f_t^i and receives from its n neighbours quality values $f_t^1, f_t^2, \ldots, f_t^n$. Consumer i wants to learn for each of the encountered consumers the corresponding probability density function $Q^m(f)$ for the f^m quality, $m = 1, \ldots, n$. Let us focus on an encountered consumer j. Given the sequence of $f_1^j, f_2^j, \ldots, f_t^j$, the probability density estimation up to t is indicated by $\hat{Q}_t^j(f)$; the subscript j is omitted in the remainder for readability reasons. The Kernel Density Estimation (KDE) method is a widely adopted non-parametric density estimation method, thus, the $\hat{Q}_t(f)$ based on t quality values $f_1, f_2, \ldots, f_t$ is

$$\hat{Q}_t(f) = \frac{1}{t}\sum_{k=1}^{t} K_h(f - f_k)$$

with $K_h(u)$ is a kernel function, which is a unimodal, symmetric, non-negative function that centres at zero and integrates to unity. The *window* h controls the degree of smoothing of the estimation. An optimal selection for h is provided by [35]. The expected value of f, $\mathbb{E}^{(t)}\{f\}$, is based on the sequence $f_1, f_2, \ldots, f_t$ and is calculated by $\int_0^1 f\hat{Q}_t(f)\,df$. Interestingly, we can incrementally evaluate the $\hat{Q}_t(f)$, that is, calculating $\hat{Q}_t(f)$ based on $\hat{Q}_{t-1}(f)$ and the observed quality value f_t at $t > 1$. Hence, consumer i does not need to store all received quality values from each encountered consumer up to time t. Specifically, we estimate the density function in the following incremental manner:

$$\begin{aligned}\hat{Q}_t(f) &= \frac{1}{t}\sum_{k=1}^{t} K_h(f - f_k)\\ &= \frac{1}{t}\left(\sum_{k=1}^{t-1} K_h(f - f_k) + K_h(f - f_t)\right)\\ &= \frac{t-1}{t}\hat{Q}_{t-1}(f) + \frac{1}{t}K_h(f - f_t)\end{aligned}$$

with $\hat{Q}_1(f) = K_h(f - f_1)$. Hence, for the expected value $\mathbb{E}^{(t)}\{f\}$, we obtain:

$$\mathbb{E}^{(t)}\{f\} = \frac{t-1}{t}\mathbb{E}^{(t-1)}\{f\} + \frac{1}{t}\int_0^1 fK_h(f - f_t)\,df. \tag{13}$$

When f_t is received, only the evaluation of $g_t(f_t) = \frac{1}{t}\int_0^1 fK_h(f - f_t)\,df$ is needed, with $\mathbb{E}^{(1)}\{f\} = g_1(f_1)$. We adopt the Gaussian kernel function $K_h(u) = \frac{1}{\sqrt{2\pi}h}e^{-\frac{1}{2}(\frac{u}{h})^2}$ and, thus,

$$\begin{aligned}g_t(f) &= \frac{1}{\sqrt{2\pi}ht}\int_0^1 ue^{-\frac{1}{2}(\frac{u-f}{h})^2}\,du\\ &= \frac{1}{\sqrt{2\pi}ht}1.253fh\left(\mathrm{erf}\left(\frac{\sqrt{2}}{2h}f\right) - \mathrm{erf}\left(\frac{\sqrt{2}}{2h}(f-1)\right)\right)\\ &\quad + h^2\left(e^{-0.5(\frac{f}{h})^2} - e^{-0.5(\frac{f-1}{h})^2}\right)\end{aligned}$$

with $\mathrm{erf}(u) = \frac{2}{\sqrt{\pi}}\int_0^u e^{-z^2}\,dz$ (the error function). Hence, the CDF of the jth encountered consumer up to tth reception of the quality value is obtained directly from $\hat{Q}_t(f)$, i.e., $\hat{P}_t(f) = \int_0^f \hat{Q}_t(u)du$. The $P^*(f)$ up to time t is then $\prod_{m=1}^{n}\hat{P}_t^{(m)}(f)$. Finally, the expectation of f^* up to time t, $\mathbb{E}^{(t)}\{f^*\}$, can be estimated incrementally in the same manner (see Eq. (13)) we estimate $\mathbb{E}^{(t)}\{f\}$ for an encountered consumer, since f_t^* is calculated at each time t.

Appendix B

In this appendix we provide the recursion for determining the scalar decision values $a_t^{(k,M)}$, $t = 1, \ldots, N$ corresponding to the (k, M) order statistic in MCFP. Based on Lemma 1, in order to obtain the recursive equation for $a_t^{(k,M)}$, we have to calculate the cumulative distribution function $P^{(k,M)}(f)$ and expectation $\mathbb{E}[f^{(k,M)}]$ of the (k, M) order statistic. $P^{(k,M)}(f)$ is calculated based on the probability

$$\begin{aligned}\mathrm{Prob}(f^{(k,M)} &\le f, f^{(k+1,M)} > f, \ldots, f^{(M,M)} > f)\\ &= \binom{M}{k}(1-f)^{M-k}f^k\end{aligned}$$

based on the assumption that quality values are uniformly distributed in [0, 1]; see Section 4. In this case, the (k, M) order statistic has a $Beta(k, M - k + 1)$ distribution, thus, we obtain

$$P^{(k,M)}(f) = \sum_{j=k}^{M}\binom{M}{j}(1-f)^{M-j}f^j$$

and

$$\mathbb{E}[f^{(k,M)}] = \frac{k}{M+1}.$$

The $a_t^{(k,M)}$ values at time t, $t = 1, \ldots, N$, are given by Lemma 1 and, in the case of MCFP, are as follows

$$a_t^{(k,M)} = a_{t+1}^{(k,M)} P^{(k,M)}(a_{t+1}^{(k,M)}) + \frac{M!}{(k-1)!(M-k)!} \times \left(B_1(k+1, M-k+1) - B_{a_{t+1}^{(k,M)}}(k+1, M-k+1)\right)$$

with terminal condition

$$a_{N-1}^{(k,M)} = \frac{k}{M+1} - \frac{1}{\zeta}$$

where $B_x(a, b) = x^a \sum_{r=0}^{\infty} \frac{(1-b)_r}{r!(a+r)} x^r$ is the incomplete Beta function and $(1-b)_r = (1-b)((1-b)+1)\cdots((1-b)+(r-1))$; the Pochhammer symbol. Hence, the optimal stopping rule for CFP_k is:

- D_1^k if $f_{t-1}^{(k,M)} > a_t^{(k,M)}$
- D_2^k if $f_{t-1}^{(k,M)} < a_t^{(k,M)}$.

If $f_{t-1}^{(k,M)} = a_t^{(k,M)}$ then both decisions are optimal. Finally, as also reported in the single CFP, a consumer adopts the CFD_k iff $a_0^{(k,M)} \geq \frac{1}{\zeta}$.

Appendix C

In this appendix we examine the expectation of quality values of context that are locally stored by a consumer adopting either CFP or MCFP. Note that, we focus only on the locally stored quality values of CFP and MCFP in order to quantify the advantage obtained from MCFP compared with CFP. An analysis on the expectation inequalities of the forwarded quality values (corresponding to the optimal stopping values) involves 'prophet inequalities' of optimal stopping theory, which is beyond of the scope of this paper.[4]

The MCFP with $K = 1$ stores all order statistics $(1, \lambda + 1), \ldots, (\lambda + 1, \lambda + 1)$, while CFP stores only the (maximum) $(\lambda + 1, \lambda + 1)$ order statistic. In this specific case, the expectations of the two maximum order statistics ($f^{(\lambda+1,\lambda+1)}$ for MCPF and f^* for CFP) for both policies are the same with $\mathbb{E}[f^{(\lambda+1,\lambda+1)}] = \mathbb{E}[f^*] = \frac{\lambda+1}{(\lambda+1)+1}$. For $K > 1$, we obtain that

$$\mathbb{E}[f^{(\lambda+K,\lambda+K)}] = \frac{\lambda+K}{\lambda+K+1} > \frac{\lambda+1}{\lambda+2} = \mathbb{E}[f^*].$$

This means that, a consumer, by adopting MCFP, stores locally context (associated with the maximum order statistic) of higher quality value than that of CFP. If we assume that a consumer communicates with a high number of neighbours, i.e., large λ, for instance, a high-density MSN, then

$$\lim_{\lambda\to\infty} \mathbb{E}[f^{(\lambda+K,\lambda+K)}] = \lim_{\lambda\to\infty} \mathbb{E}[f^*] = 1.$$

In such case, we obtain the same expected quality values by both policies for context associated with the maximum order statistic. In addition, if we store a high number of quality values of pieces of context, i.e., large K, in MCFP, then we obtain expected value $\mathbb{E}[f^{(\lambda+K,\lambda+K)}] = 1$ as $K \to \infty$. Finally, the mean value of the expected values of the order statistics $(1, \lambda + K), (2, \lambda + K), \ldots, (\lambda + K - 1, \lambda + K)$, i.e., excluding the maximum order statistic, in MCFP is

$$\begin{aligned}\frac{1}{\lambda+K-1}\sum_{k=1}^{\lambda+K-1} \mathbb{E}[f^{(k,\lambda+K)}] &= \frac{1}{\lambda+K-1}\sum_{k=1}^{\lambda+K-1} \frac{k}{\lambda+K+1} \\ &= \frac{1}{(\lambda+K-1)(\lambda+K+1)}\sum_{k=1}^{\lambda+K-1} k \\ &= \frac{\lambda+K}{2(\lambda+K+1)} = \frac{1}{2}\mathbb{E}[f^{(\lambda+K,\lambda+K)}].\end{aligned}$$

This quantifies the *additional* quality value of pieces of context that are circulated in a MSN when consumers adopt MCFP. In CFP, we obtain only quality values that correspond to the maximum order statistic.

[4] The interested reader could refer to T.P. Hill, R.P. Kertz, 'A survey of prophet inequalities in optimal stopping theory', Contemporary Mathematics, 125(1):191–207, Jan., 1992.

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