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Opportunistic Forward Routing Using Bee Colony Optimization

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Abstract— An intermittent connectivity experience node by paradigm of opportunistic forwarding has been proposed to serve emerging wireless networking applications transmit messages to a distant destination for given delay bound, disjoined parts of the network exchange information by nodes broker to exploit node mobility. Forwarding decision is made by main challenge of opportunistic forwarding relays the best chosen cumulative probability within the delay bound of destination. The Bee Colony algorithm performs a kind of neighborhood search to solve this issue at recent work combined with global search used for both combined optimization and continuous optimization. Choosing initial centroid clusters is the problem for OFPC affects the efficiency of algorithm. The initial centroids for clusters are found to introduce by Bee Colony algorithm. A new opportunistic forwarding scheme is designed after finding the initial centroid, partial centrality with opportunistic forwarding (OFPC), and theoretically quantifies the partial centrality influence on the data forwarding performance using Bee colony optimization. Bee Colony optimization creates multi agent system capable to successfully solved difficult combinatorial optimization problem as the basic idea. Different TTL requirements are epidemic by applying our scheme on three real opportunistic networking scenarios, our extensive evaluations show that our scheme achieves significantly better mean delivery delay and cost compared to the state-of-the-art works, achieve delivery ratios sufficiently closer. The OFPC outperforms other solutions overall with extending shows the evaluation result, especially in terms of mean delivery delay and cost.

Keywords—Opportunistic Forwarding with Partial Centrality, Bee Colony algorithm, clustering, opportunistic networking scenarios, Decayed Aggregation Graph

I. INTRODUCTION

Mobile and static sensors, user cell phones, and vehicles replete world leading with technology advances equipped with a variety of sensing and computing devices, multitude opportunities for pair wise device paved the way for contacts. Content, resources, and services are shared each other by Opportunistic computing exploits the opportunistic communication between pairs of devices (and applications executing on them). Real-life application problems opens for opportunistic routing as exciting avenue for research and development, one hitherto not fully exploited, and at the same time expands the potential of opportunistic networks and it combined with social computing as new paradigm of opportunistic computing with pervasive applications. Opportunistic computing recognizes and exploits users' social behavior whenever pervasive computing seeks to enhance user quality of life through proactive application services. Computing, communication, storage, energy, sensing, and related applications are terms of complementary capabilities with user devices and indeed with BANs/PANs. A set of middleware services are opened for developing several lines of research mask disconnections and heterogeneities provide the applications with data uniform access and services in a disconnected environment. Lacking global knowledge of the network topology, data forwarding decisions are made by adopting various heuristics as inferring the likelihood of forwarding the message (e.g., [1] [2] [3]), employing the contact locations (e.g., [4]), or contact frequencies [5] focusing the unstable end-to-end early works. The prediction of physical contact metrics1 of nodes guarantees packet delivery solutions obviously. The underlying mobility process argues solutions which are not cost effective with opportunistic scenarios reflect facet of simple metrics in opportunistic scenarios. Human walks heavily affect the network performance [6] [7], e.g., devices lose connection when people move around (in the rest of this paper, without loss of generality, we use the terms "people" and "node" interchangeably) with the recent popularization of personal hand-held mobile devices. The inherent characteristics of the network structure are captured to believe by social contact metrics achieved by complex network analysis [8], and are less volatile than the physical contact metrics. Integrating social metrics are focused into the opportunistic forwarding algorithms are motivated by observation in this article. Intermittently connected environment are design to turn critical when challenging especially. The opportunistic forwarding decision formulates few attempts to explicitly make use of social metrics recently. The three most recent works are SimBet [9], Bubble [10] and People Rank [11]. 1) People with closer relationship tend to Residing communities are tend to people with closer relationship and 2) different popularity within people community are the detailed forwarding schemes differ by the motivation of two important observations from society. "Central" nodes are more probably chosen as carriers to relay messages between disconnected communities [12] [13] increasing as "popular", until a node belonging to the same community with the destination is reached [12] [13]. Opportunistic forwarding algorithms are not explicitly "social based" when information about community structure and node popularity enables them to outperform well-known intuitively. All three protocols prefer to use global measures of node centrality noticed that (e.g., exploiting ego networks in [12], between centrality in [13] and Page Rank [16] algorithm in [14]), when each node is ranked with respect to all other nodes in the network. High global node centrality is not the appropriate relay candidates, to argue these possible nodes probably due to the fact of such nodes have low importance relative to a specific subset of nodes, when the destination belongs. High relative importance to the community partners of destination bear most weight on routing performance interestingly when nodes have low global centrality to exhibit it.

Fine-grained relations provide relative importance among nodes helps to make informed forwarding decisions (e.g., a node is just the desired relay, if it exhibits a highly relative importance to the destination's community partners). The partial centrality metric are employed initially at end to measure the relative importance of node with respect to such nodes within a community. Partial centrality metric and community structure are improved by opportunistic forwarding efficiency by developing an opportunistic forwarding scheme to summarize our contributions as follows:

• The partial centrality metric evaluate the performance of opportunistic routing. Integrating social metric into opportunistic routing is the initial attempt for the best of our knowledge.

• Node's partial centrality in a distributed fashion is proposed for online method to compute makes our work more applicable. The overlapped community structure are detected effectively distinguish the bridging nodes from other nodes, exploit the community structure label the community partners of destination.

• Decayed Sum Problem [18] is formulated for strength of relationship between nodes use a Decayed Aggregation Graph (DAG) dynamically model for network topology.

• Bee colony optimization is used for data forwarding performance with theoretically quantify the influence of partial centrality to implement OFPC to create multi agent system successfully solved capably difficult combinatorial optimization problem. Three real opportunistic networking scenarios are compared for several state-of the-art works in it. The OFPC outperforms other solutions is an extensive evaluation results, especially in terms of mean delivery delay and cost.

This paper is remained to organize as follows. The related work comprises section II. The network model and forwarding scheme are described by section III. Performance evaluations are made by section IV. Section V drawn out for conclusion.

II. RELATED WORK

A lot of opportunistic forwarding algorithms are proposed earlier classifies them into the two categories based on the contexts they used. Epidemic forwarding styles for partially connected ad hoc networks [31] are proposed initially by A. Vahdat and D. Becker termed as Physical contact tried to grasp each forwarding opportunity guarantee high packet delivery ratio consumes more system resources as well. Other forwarding mechanisms (e.g, [4] [7] [8]) are developed by deficiency of motivated researchers. The networking performance depends heavily on the contexts utilized to identify "the best" relay node for destination. A probabilistic routing protocol for opportunistic networks is presented for prophet presented by A. Lindgren et al. [4] in this example. The probability of future encounters are exploited for past contact moments to predict it. A high-dimensional Euclidean space constructed for Moby space proposed by J.Leguay et al. [7] for the past contact locations similarly. The delivery delays are increased by reducing these schemes of overhead apparently. Social structures evolve from human activities are not considered for the aforementioned physical contact based scheme are noted as Social contact based. The hand-held mobile devices with recent personal popularization, networking performance are played for critical role gradually in human mobility, strong spatiotemporal correlation (e.g., clustering) [9] [10] are shows for human walks, instead of purely random motions. Social structure on opportunistic communication are influenced to focus recent researchers consider the fact. Centrality/similarity metric exploit social structures for instance proposed by E. Daly, P. Hui and A. Mtibaa et al. [12] [13] [14] to make forwarding decisions. High centrality/similarity metrics forward messages relatively with nodes to increase the probability of finding better relays of final destination. Each node evaluates its Centrality evaluates each node and ego network technology contains similarity metrics, and carries message either forwarded to nodes which have higher similarities with the destination node, or relay with the most central node presented by SimBet [12] as example. A message is relayed across nodes as same in Bubble [13] with increasing centrality metrics still it enters into the range of the destination community. PageRank [16] algorithm is exploited by PeopleRank proposed by Mtibaa et al. [14] to evaluate node centrality, and forward message to such nodes with higher centralities than current carriers. The impacts of partial centrality metric are explored by main difference between our work and state-of-the-art works for performing opportunistic routing. Forwarding decisions are made by informed to help novel metric made here.

III. NETWORK MODEL

Relevant details should be given including experimental design and the technique (s) used along with appropriate statistical methods used clearly along with the year of experimentation (field and laboratory).

Decayed Aggregation Graph (DAG) $\mathrm{G} = (\mathrm{V}, \mathrm{E})$ is an opportunistic network model presented here, where set of nodes are denoted by V and E denotes the set of edges. Adjacency matrix are denoted by $\mathrm{W}(\mathrm{t}) = (\mathrm{w}_{\mathrm{uv}}(\mathrm{t}))_{\mathrm{n}\times\mathrm{n}}$ and contact series are denoted by $\mathrm{N}_{\mathrm{uv}}((\mathrm{t}) = \{(\mathrm{on}_{\mathrm{i}}, \mathrm{off}_{\mathrm{i}})\ \mathrm{i} = 1,2,\ldots,\mathrm{N}\}$ between nodes u and v at moment t, where the start moment and end moment of the ith contact are denoted by tuple $(\mathrm{on}_{\mathrm{i}}, \mathrm{off}_{\mathrm{i}})$ respectively, and number of contacts denotes N. Strength of relationship between nodes (i.e., the value of$\mathrm{w}_{\mathrm{uv}}(\mathrm{t})$ are computed to formulate as a Decayed Sum Problem. of$\mathrm{N}_{\mathrm{uv}}((\mathrm{t})$ is the goal is to estimate the decayed sum at any current time T.

$$w_{uv}(T) = \sum_{i=1}^{N} f(i) g^{(T-off_i)}$$

For the given contact series as the definition 1 of decayed sum Where i^{th} contact duration are denoted by $\mathrm{f(i)} = \mathrm{off}_{\mathrm{i}} - \mathrm{oni}$ and decayed function are denoted by $\mathrm{g}(\mathrm{T} - \mathrm{off}_{\mathrm{i}}).\ \mathrm{g}(\mathrm{T} - \mathrm{off}_{\mathrm{i}}) = \mathrm{e}(-\_ \times (\mathrm{T} - \mathrm{off}_{\mathrm{i}}))$ are set in this article, follows an exponential decay[20] generally for inter-contact time. The space complexity of DAG are analysed by equation to reformulate

$$w_{uv}(T) = \textstyle\sum_{i=1}^{N} (off_i - on_i) e^{-\beta(T-off_i)}$$

$\mathrm{w}_{\mathrm{uv}}(\mathrm{T})$ Exact tracking strategy needs $\Theta(\mathrm{N})$ storage bits. Calculation precisions are similarly kept for storage overhead to reduce considerable scalability issue (in general, $\mathrm{N} \gg \mathrm{n}$). The following lemma are obtained by $\mathrm{h(t)} = \mathrm{off}_{\mathrm{i}} - \mathrm{on}_{\mathrm{i}}$ if and only if t equals to $\mathrm{off}_{\mathrm{i}}$, otherwise,$\mathrm{h(t)} = 0$. Eq. (2) is equivalent to the following Equation (3) in Lemma 1 as continuous interval [0,T].

$$w_{uv}(T) = \sum_{t \le T} h(t) e^{-\beta(T-t)}$$

Opportunistic Forwarding with Partial Centrality with ABC: OFPC algorithm is presented here. Informed forwarding decisions are made for OFPC to combine the knowledge of node partial centrality and that of overlapped community structure. Algorithm is behind to be intuited with two. Different social roles are played for the same person initially relative to different groups. Higher partial centrality metrics are nodes with one component of OFPC is to forward message for the destination communities than the current relay. Different social behaviours are shown for people in society at the next step. One clique is sometimes tending to form in their social lives. Multiple cliques are joined for other likes and few people prefer to stay at home. Various types of nodes are related to other component of OFPC make different forwarding decisions. The algorithm is formed by combining two components. They can serve as postman for the passing communities when nodes pass different communities if there is extra storage space. BEEINFO imitates bee searching process for inter-community to perceive node's influence different community. Bees search the nectars in artificial bee colony algorithm and back to hive when ring the biggest density nectar. Nectar densities are being aware by capable for bees. Three nectar sources (Source A, Source Band Source C) are shown at Fig.2 goes for scout bee with different densities and every source ID, density are recorded compares the densities to get the maximum. BEEINFO-D&S are the core for forwarding strategy. Density or social tie is predicted to encounter for future here for choosing the best forwarder. The information is obtained for BEEINFO-D&S are easier for destination information (i.e. ID and interest) is stored in the message header. BEEINFO-D&S classifies the environment context related to the interest of DN, SN and IN into inter-community and intra-community takes different measures. The forwarding strategy are given by pseudo code of algorithm 2 describe all the possible situations to explain the algorithm

1) DN, SN, and IN have the same interest when $\mathrm{Is} == \mathrm{Id}$ and $\mathrm{Ii} == \mathrm{Id}$, means they are all in the same community. The social tie will be utilized to decide intra-community for the better forwarder. The social tie about DN maintain to contact DN both by SN and IN respectively. The better forwarders are selected for node with high socialite. The forwarding process are stopped when neither has the social tie record for DN in order to wait for better forwarder

2) DN and SN share the same interest, where IN has the different interest when $\mathrm{Is} == \mathrm{Id}$ and $\mathrm{Ii} \mathrel{!}= \mathrm{Id}$. DN and SN is similar community, and IN is an outside node. This

situation suggests we need a node in the same community to perform Intra-community forwarding, are suggested to use a node in same community to perform and IN is not suitable to be forwarder.

3) IN and DN have the same interest but SN has the different interest based on Is! = Id and Ii == Id . IN and DN are similar community, but SN do not involve to them. And select forwarding strategy as a forwarder and the message of IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY 8 forwards from SN to IN.

4) SN and IN have the same interest in case of Is ! = Id and Is == Ii, when DN's interest differs from the others'. It indicates that SN and IN are indicated for the same community not for the destination community and also an inter-community forwarding. The forwarder selects to utilize for density information. The higher density of node DN chose as forwarder between SN and IN.
5) IN and DN share on common interests for Is ! = Id and Ii ! = Id andIs ! = Ii: SN at all, differ communities and also an inter-community environment too. Forwarder chooses last condition of same procedure to perform in BEEINFO-D&S. BEEINFO-D neglect the collection of social tie information and this strategy involves 4) and 5).
Density information of communities is not considered for BEEINFO-S. 1) And 3) denoted the forwarding strategy. Response message are broadcast when all destination node receives the messages to notify the nodes still maintains the message to discard it. The data are stored with higher probabilities to response messages with more efficient for nearby nodes.
Short TTL control for response messages and it can optimize message by discarding buffer management.
Message Scheduling and Buffer Management: Power, buffer size and contact time are the scarce resources restricted to mobile nodes effect the routing and forwarding efficiency. Transmit rate, reduce buffer replacement, lower drop rate, and save resource are improved for buffer management and message scheduling to perform BEEINFO. The messages are transmitted to decide message scheduling strategy between nodes with the least time cost. Higher opportunities can be successfully delivered when ensuring messages. When the buffer reaches its capacity and new messages requires buffer discard messages to decide Buffer management algorithm. Excluding or discarding the messages are expired or delivered successfully to require same principle of both Message scheduling strategy and buffer replacement algorithm without influencing messages in transmission and the difference only lies in the sequence. We choose to describe as a result together in this section and the details are as follows. The relation between the DN and IN is the major force to select IN as forwarder and relevant messages are waiting to be delivered for measuring the success rate. Set of messages assume to be transmitted. The messages order for message scheduling strategy according to the following priority rules.

1. The messages will be transmitted initially if they satisfy Id == Ii when intra-community transmission has higher priority. The social tie between DN and IN will be taken into consideration when messages constraint to be same condition. DN will have higher priority when messages have higher social tie. The newer one will be transmitted initially for social tie which is equal.

2. The inter-community transmission suits for messages that do not satisfy the condition Id == Ii considers for density of different interests in IN. The messages will be reordered according to density values when IN has different densities to different communities. The newer one will be transmitted initially when messages have equal value. SN and the messages rely for buffer replacement algorithm. DN and SN relations are mainly considered here. The reverse orders with the scheduling sequence are followed when it has principle of buffer replacement algorithm.

1. SN's community is replaced to send out the messages initially termed as inter-community forwarding. The densities of different DNs in SN consist of messages further decide the sequence to be replaced. Initially messages are discarded with low density. The older one will be replaced when densities are equal.

2. The messages where Id is equal to Is are considered next, and message with the lowest social tie of DN in SN will be discarded initially. The older one will be replaced when the social ties are equal to each other. 1) Strong nodes (nodes only belonging to one community), 2) bridging nodes (nodes belonging to multiple communities) and 3) noise nodes (nodes not belonging to any community) are three categories of nodes which classify for algorithm. More formal definitions are referring to section III.C. OFPC-BEE describe for the baseline implementation next. Node u and node v are taken as samples. Node v deliver it when node u meets node v, for any message m that u carries, if its destination md is node v, node u delivers it to and removes it from u's message queue. Node u makes different forwarding decisions when node v does not hold this message based on the categories belong to.

(1) Node v is a noise node: The message m to node v does not forward for node u.
(2) Node u is a noise node, but node v is a strong or bridging node: Buffer deletes m when node u forwards m to node v.
(3) Neither u nor v is a noise node: Partial centrality metrics (relative to the community partners of destination) are higher if message m does not deliver the community of destination which belongs to forward such nodes than the current relay still it reaches a node which shares a community with the destination node. Higher partial centrality metrics forward the message of community members until the destination

receives it or it expires. Cost reduction clear m with original carriers from their buffer when m enters into the community2 and this process is done by algorithm 2, where _ denotes the null set, Partial centrality of node u denoted by PCu, node u's set of community labels denoted by Com (u) and two nodes u and md denote $(\text{com}(u) \wedge \text{com}(m_d) == \emptyset)$ belong to the same community, or it does not share one community.

Algorithm OFPC BEE

$Upon\ meeting\ up\ up\ node\ v\ do$
$given\ message\ M\ in\ the\ buffer\ of\ node$
$For\ all\ IN\ do\ if\ I\ IN\ /$
$/N\ is\ DN\ then\ deliver\ M\ from\ SN\ //$
$else\ if\ I\ i == Id$
$then\ //IN\ belongs\ to\ destination\ community$
$if\ SoTie()SN, DN < SoTie(IN, DN)$
$then\ Deliver\ M\ from\ SN\ to\ IN;$
$end\ if$
$Is\ Is! = Id\ then\ //Ii! = Id\ and\ Is! = Id$
$if\ density\ of\ SN$
$<\ density\ of\ IN\ for\ Id\ then\ Deliver\ M\ from\ SN\ to\ IN;$
$for\ any\ message\ m\ in\ u\text{'s}\ queue\ do$
$if\ (m$
$\notin v.queue) then\ if\ (neither\ u\ nor\ v\ is\ a\ noise\ node) then$
$if (com(u) \wedge\ com(m_d) ==\ \emptyset)\ and\ (com(v) \wedge\ com(m_d)$
$==\ \emptyset)\ and\ (PC_u < PC_v)\ then$
$m \to v$
$end\ if$
$if (com(u) \wedge\ com(m_d) \neq\ \emptyset)\ and\ (com(v) \wedge com(m_d)$
$\neq\ \emptyset)\ and\ (PC_u < PC_v)\ then$
$m \to v$
$end\ if$
$end\ if$
$end\ if$
$if\ (m \in v.queue)\ and\ (com(v) \wedge com(m_d)$
$\neq\ \emptyset)\ and\ com(u) \wedge\ com(m_d) =$
$=\ \emptyset)\ and\ (w_{um_d}$
$< w_{vm_d})\ then\ \ u.Remove(m)$
$end\ if$
$end\ if$
$end\ if$
$end\ for$
$end\ if$
$end\ if$

The following two sections bought the evaluation of detailed partial centrality and the detection of overlapped community structure, respectively.

Evaluating Partial Centrality: The partial centralities of a node relative to the community members and are mainly focused to mention it. Node centralities are computed not applicable for traditional solutions for unknown number of neighbours and vulnerable end-to-end path in opportunistic networks. The partial centralities metric are deal with use of technology Principal Component Analysis (PCA) [17] to detect the overlapped community structure.

Principal Component Analysis: Extract relevant information from a data set is formed by powerful tool of PCA by filtering noise and redundant data. The hidden, simplified structures contain relevant information underlying the data set. The principles of PCA are generalized as follows. A node u has built the matrix W from view of the DAG (please refer to Section II.B), and the matrix W is centralized (i.e., subtract the corresponding mean from each of columns). The covariance matrix of W is denoted by CW = $W^T W/(n-1)$.

$$P^T C_W P = \Lambda$$

where Λ = diag (1, 2, ..., n) and P is a normalized orthogonal further diagonalizable the CW.

Algorithm 2 PCA

1: Input: an adjacency matrix W of DAG
2: Output: orthogonal matrix P and diagonalied matrix Λ
3: $W =$ centralized(W)
4: $C_{W=\text{cov}(W)}$
5: $[P, A] \leftarrow \text{eigs}(C_W, n)$

Let matrix $P_k = (x_1, x_2, ..., x_k)$ and Λ k =diag(1, 2, ..., k). Let $\alpha_u^+ = (|\alpha_{u1}|, |\alpha_{u2}|, ..., |\alpha_{ui}|, ..., |\alpha_{uk}|)$,where $|\alpha_{ui}|$ denotes the absolute value of α_{ui} mathematically, Decayed aggregation graph G with k communities, the projection matrix of P_k, the vector α_u^+presents the likelihood of node u's attachment to such k communities are termed as Lemma 2. The Overlapped Community Structure is detected to cut graph into small clusters learned widely. Overlapped community structures are extended by testing the k-means with well-known clustering algorithms. CNM and k-clique does not need to know the neighbour relationship between nodes are the advantages of k-means algorithm compared to other methods, and DAG represents for requirement of adjacent matrix of a weighted graph, where CNM and k-clique are more appropriate to a binary graph. The numbers of communities, the initial elements for each community and the termination condition, three issues strongly affecting the performance of k-means are based on the technology of PCA additionally and it detect the overlapped community structure based on the refined k-means.

Determining k, the number of communities: Confusing data set is reduced for roadmap to provide PCA as a lower dimension retains the main features of the original data set. The Eigen values of a network play a big role in many important graph features as the relation behind it. The maximum degree, clique number, and the randomness of a graph are all shown to be related as λ_1. The main structures of the graph are denoted to select the top k eigenvectors, where k value satisfies P_{ki}=1_i,Pnj=1_j ≥ R (13)and the ratio R involved in interval [0.7, 0.9] [17]. The main structures of a network (please refer to the Section IV.A) are enough to characterize set R=0.85 set in this article.

Identifying the noise nodes: 1) the principal components Pk, and 2) the opposite Pk+1, where the Pk+1 = (xk+1, xk+2, ..., xn) are two different parts of PCA divides a network shown in Fig.2 and later represents noise components of the network. We divide the row vector _u by_1,ku (_u1, _u2, ..., _uk) and _k+1,nu (_u,k+1, _u,k+2, ..., _un),the signal and noise of the node u and it identifies whether a node is a noise node or not. (Node u's signal−to−noise ratio SNRu): SNRu =Pi∈[1,k] (_i_ui)2.Pj∈[k+1,n] (_j_uj)2 shows definition 2. Node u's partial centrality relative to community i is |_ui| _i, which is the amplitude of node u's signal in the ith dimensional spectral space are known from the theorem 2. Eusignal =Pi∈[1,k] (_i |_ui|)2 =Pi∈[1,k] (_i_ui)2 represents the signal energy eusignal of node u ,and Pj∈[k+1,n] (_j_uj)2 equals for noise strength of eunoise and propose the following definition. The node u is a noise node if its SNRu satisfies SNRu < 1 is termed as Noise Nodes presented by definition 3.Determining the initial elements for each community: The noise nodes are excluded after ascertain the number of communities to determine the initial centroid mi(i = 1, 2, ..., k) for each community. The initial node of community i are selected as node of u, s.t. max |_ui| (u = 1, 2, ..., n) for each eigen vector xi, and set mi = _u describes this procedure at algorithm 3.

Termination condition of k-means: All non noise nodes are clustered, and mi is updated bymi =_Xu⊂Ci_u_/ni (14) where ni is the number of nodes only belong to Ci (i.e., node u is a strong node in Definition 4). Minimizing the sum of squared errors are characterized by k-means, J =Xki=1Xu⊂Ci (_u −mi)2 (15). The greedy natures of the update strategy are done by the standard iterative method to suffer k-means seriously from the local minima problem. K-means immune problem are guaranteed for PCA fortunately at theorem 4. J is minimized equivalent to maximizing trace (PTCWP), and max trace (PTCWP) = _1 + _2 + ... + _k at Theorem 4. The PCA-based k-means reaches the optimal performance once we cluster the non-noise nodes for the first time.

Detecting the overlapped community structure

Multiple communities are joined to allow non-noise node in this article and the nodes are 1) strong nodes and 2) bridging nodes classifies the two categories. Strong node if it is a node u only belongs to one community is termed as Strong Nodes and represented by definition 4. Bridging node if it joins two or multiple communities in node u is termed as Bridging Nodes represented by definition 5. The following steps now discuss how to identify the online strong and bridging nodes.

(1) Clustering nodes: The distance between itself and the centroid mi, dist(_u,mi), and select i, s.t. min dist(_u,mi) (i = 1, 2, ...k) as the community node u are computed belongs to, where, dist(_u,mi) = _(u, i) = arccos_umiTk_uk 2 kmik 2and _(u, i) denotes the angle between _u and mi for any node u. Strong node are labeled by node u and update mi by Equation. For other_(u, j) (j 6= i, j = 1, 2, ...k), Bridging node belonging to community j are labeled as node u, if and only if the _(u, j) ∈[_/4−', _/4+'] (please refer to Theorem 5), where ' is the overlapped coefficient and clustering procedure are represented by algorithm 4.

(2) Adjusting the categories of nodes: The blurred labels of nodes and explicit community structure are detected together after step (1) finished. Multiple communities are shared by some of the nodes with strong labels "bridging" only involved in community; such are labelled with strong and bridging repeatedly. We need to re-classify each node for end. The number of communities node u are denoted by Com | (u) | belongs to Algorithm5 presents the adjusting process.

Determining the overlapped interval [_/4 − ', _/4 + ']: The overlapped set was focuses on this section.

IV. DATASET AND EXPERIMENTAL RESULT

The overlapped community structures are analysed by underlying the data-sets and then compare the performance of OFPC initially used with two state-of-the-art works: Benchmarks is denoted by Bubble and Prophet [4] together with the Epidemic [11] and Direct Contact [3] algorithms. Social-based forwarding algorithm also called Bubble and IETF draft [20] as Prophet. Mean delivery delay, cost and packet delivery ratio are the performance evaluation metrics with important bound of upper and lower results to Epidemic and Direct algorithms.

A. Data-sets: North Carolina State Fair, NCSU, and KAIST are referred to gather three real data-sets . Intra/inter-contact distribution are the characteristics of data-sets explored in several studies and applied into different scenarios [18] [19]. Rich diversity of environments are find to cover and analyse these traces ranging from well-connected scenario (State fair) to quite sparse situation (NCSU). Evaluate the performance.

Mean delivery delay (MDD): Different message TTLs are shown at Fig.1 to illustrate the performance of mean delivery and also obviously shown that OFPC expedites the dissemination speed of message. 70%improvement in MDD over Prophet and 40% over Bubble at State fair are achieved in an suitable example. OFPC exploits the partial centrality metric to make Forwarding decisions are made by OPFC to exploit the partial centrality metric, the relations between nodes are characterized for level8 provides fine-grained of novel metric helps to choose the more qualified relays than the centrality-based scheme does is the main reason behind it. Cost: Fig.6 OFPC provides best performance clarifies at Fig.6 in term of cost as well. OFPC helps to reduce up to 2× and 3× over head in Bubble and Prophet at the example of state fair. OFPC still outperforms Bubble and Prophet at very sparse scenario of NCSU (Fig.1 (b)) occurs because 1) delivery delay are improved for helping partial centrality metric to reduce the cost, and 2) noise nodes are excluded from the relay candidates are isolated and far away from the community members (please refer to Section III.A).Packet delivery ratio (PDR): the performance of packet delivery ratio are shown by Fig.2. OFPC attain same delivery ratio to Bubble, and both of the mout perform the Prophet.

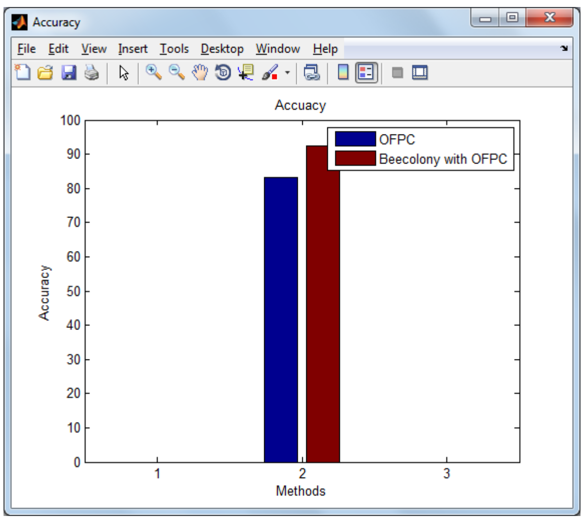

Figure 1. Performance of mean delivery

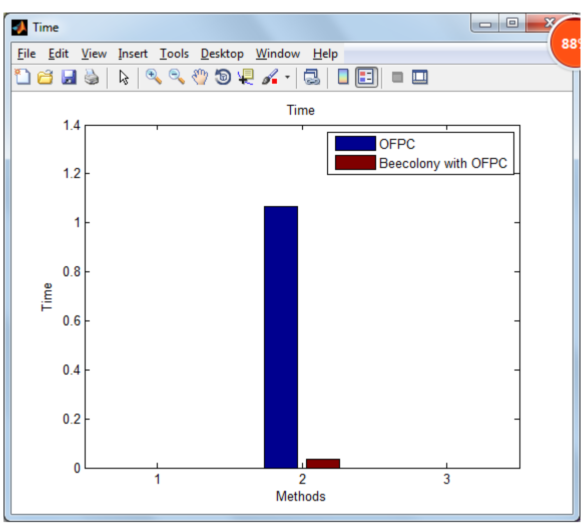

Figure 2. Packet delivery delay

V. Conclusion and Future Scope

The main conclusions of the study may be presented in a short Conclusion Section. In this section, the author(s) should also briefly discuss the limitations of the research and Future Scope for improvement.

Opportunistic routing is improved by the performance of Bee colony optimization for OFPC, a partial centrality metric based forwarding algorithm described in this paper. The bee colony was implemented initially to perform centrality and calculate community labels of noise node in proposed article. Finding of clustering nodes is to calculate community labels provides next step. After adjusting the node's categories technology from PCA and k- Means algorithm, the clustering nodes are found by using the initial centroid method. Trace-driven simulations finally validate the effectiveness of method. OFPC is computationally more efficient than existing works when result efficiency analysis and simulation shows for Bee colony optimization and also processing time is reduced. Bee colony optimization for OFPC improves the forwarding technique as future work in this article.

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