A paradigm for the cooperation of objects belonging to different IoTs

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ABSTRACT

The Internet of Things (IoT) is currently considered the new frontier of the Internet. One of the most effective ways to investigate and implement IoT is based on the use of the social network paradigm. In the last years, social network researchers have introduced new models capable of capturing the growing complexity of this scenario. One of the most known of them is the Social Internetworking System, which models a scenario comprising several related social networks. In this paper, we investigate the possibility of applying the ideas characterizing the Social Internetworking System to IoT and we propose a new paradigm capable of modelling this scenario and of favoring the cooperation of objects belonging to different IoTs. Furthermore, in order to give an idea of both the potentialities and the complexity of this new paradigm, we illustrate in more detail one of the most interesting issues regarding it, namely the redefinition of the betweenness centrality measure.

KEYWORDS

Internet of Things, Social Internetworking System, Cross Nodes, Cross Edges, Inner Betweenness Centrality, Cross Betweenness Centrality

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1 INTRODUCTION

The Internet of Things (IoT) can be considered as an evolution of the Internet, based on the pervasive computing concept [7]. In the past, several strategies to implement the IoT paradigm and to guarantee ubiquitous computing have been proposed [19, 28, 52]. One of the most effective of them is based on the use of the social networking paradigm [5, 6, 8]. In this case, IoT is represented as a social network and, thanks to this association, Social Network Analysis-based models can be used to empower IoT.

In [17, 43], some of us introduced the concept of Social Internetworking System (SIS, for short) as a system comprising an undefined number of users, social networks and resources. The SIS paradigm was thought to extend the Online Social Network (OSN) paradigm by taking into account that: *(i)* a user can join many OSNs, *(ii)* these joins can often vary over time, and *(iii)* the presence of users joining more OSNs can favor the cooperation of users, who do not join the same OSNs. We think that the key concepts of SIS can also be applied to things (instead of to users) and to relationships between things and, in this paper, we propose a paradigm to handle the cooperation of things belonging to different IoTs. For this purpose, we introduce the concept of Multiple IoT Environment (hereafter, MIE). It can be seen as a set of things connected to each other by several kinds of relationship and, at the same time, as a set of correlated IoTs, one for each kind of relationship into consideration. In a MIE, there is a node for each thing; furthermore, there is an edge between two nodes if the corresponding things are linked by a relationship. If more kinds of relationship exist between two things, then more edges exist between the corresponding nodes, one for each kind of relationship. All the nodes linked by a given kind of relationship, together with the corresponding edges, form an IoT of the MIE.

IoTs are interconnected thanks to those nodes corresponding to things involved in more than one kind of relationship. We call *cross nodes* (*c-nodes*, for short) these nodes and *inner nodes* (*i-nodes*, for short) all the other ones. Then, a c-node connects at least two IoTs of the MIE and plays a key role to favor the cooperation among i-nodes belonging to different IoTs. As a consequence, the nodes of a MIE are not all equal: c-nodes will presumably play a more important role than i-nodes for supporting the activities in a MIE.

Once a MIE has been defined, it is possible to apply Social Network Analysis-based techniques on it for extracting powerful knowledge concerning its things, their relationships, the IoTs formed by them, etc. In order to show how the issues typical of Social Network Analysis can be extended to a MIE, in this paper, we illustrate the case of betweenness centrality. This measure starts from the assumption that a node of a network can gain power if

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it presides over a communication bottleneck. The more the other network nodes depend on it to make connections with each other, the higher its power.

The betweenness centrality of a node in a network is defined as the fraction of the shortest paths between all the pairs of network nodes that pass through it. Betweenness centrality is well suited for measuring the influence of a node over the information spread through the network [10, 39], to identify boundary spanners (i.e., nodes acting as bridges between two or more subnetworks), and to measure the "stress" (in the sense of a higher usage) that a node must undergo during network activities [13, 14, 18, 24]. Due to its relevance in network analysis, betweenness centrality has been largely investigated in the past, and several extensions, tailored to specific contexts, have been proposed (see, for instance, [12, 20, 21, 50]). However, the classical betweenness centrality is not able to capture the centrality of c-nodes w.r.t. paths crossing different IoTs. In other words, it is not able to distinguish c-nodes from i-nodes and to evidence the key role played by c-nodes in favoring communication and cooperation between things belonging to different IoTs of the MIE.

For this reason, we propose two new measures of betweenness centrality, well suited for a MIE and, more in general, for a scenario consisting of a set of related IoTs. These measures are called *Inner Betweenness Centrality* (IBC, for short) and *Cross Betweenness Centrality* (CBC, for short). They have been designed to clearly distinguish the contributions of c-nodes and i-nodes and are able to find central nodes belonging to a specific type. In particular, IBC has been conceived for measuring the betweenness centrality with a focus on a single IoT of the MIE and it privileges i-nodes over c-nodes. As it will be clear in the following, it does not coincide with classical betweenness centrality because, differently from this last one, it distinguishes i-nodes from c-nodes. By contrast, CBC is specialized to measure the betweenness centrality of nodes by privileging paths involving more IoTs of the MIE and, therefore, c-nodes over i-nodes.

This paper is organized as follows: in Section 2, we illustrate related literature. In Section 3, we present our paradigm. In Section 4, we illustrate our proposal to redefine the betweenness centrality measure. Finally, in Section 5, we draw our conclusions and have a look at some future developments of our research efforts in this area.

2 RELATED LITERATURE

Several years have passed since the IoT paradigm was introduced [4, 7, 38, 45]. During this period, the term "Internet of Things – IoT" has been associated with a huge variety of concepts, technologies and solutions. For instance, in the last few years, new technologies, such as Big Data and Social Networking, have been applied to IoT. They have changed, and are currently changing, the very definition of this term. What IoT will become in the future depends on the evolution of all these technologies.

The current research on IoT focuses on the capability of connecting every object to the Internet. This way of thinking IoT led to the Web of Things paradigm [28, 29, 31] and to the application of Social Networking to the IoT domain [6]. In the next future, these technologies will be combined with other ones, such as Information Centric Networks [3, 48, 52, 53] and Cloud [19, 33, 49]. As a matter of fact, the strengths of these ones are exactly the features necessary to overcome the weaknesses of the current IoT concept [51]. Some examples of this combination can be already found in the literature [22, 26].

Significant efforts have been made to apply the Social Networking ideas to the IoT domain. Actually, the implementation of reliable IoT passes through the definition of a complex architecture capable of managing services, enabling a complete connectivity among things, guaranteing quick reactions to frequent state variations and, finally, ensuring a good scalability [5].

The first attempts to apply Social Networking to the IoT domain can be found in [27, 30, 35, 40]. In these papers, the authors propose to use human social network relationships to share services provided by a set of things. An important step forward is performed in [5], where the SIoT paradigm is introduced. Here, the authors propose an approach to creating relationships among things, without requiring the owner intervention. Thanks to this idea, things can autonomously crawl the network to find services and resources of their interest provided by other things. In [8], the same authors clearly highlight what are the main strengths of SIoT.

In [6], the authors point out that there are still several open issues that must be investigated in the SIoT paradigm. In particular, making things capable of establishing heterogeneous social relationships requires specific investigations and new approaches. Among them, the most relevant ones for our context are: *(i) Defining inter-objects relationships.* This task requires a correct digital representation of an object and the definition of a methodological and technological solution capable of crawling and discovering other (possibly heterogeneous) objects, with which interactions can be established. *(ii) Modeling the new social graphs thus obtained* in such a way as to characterize them and to define new algorithms for performing their analysis.

Today, the connection level of humans and things is continuously increasing so that it appears reasonable to start to investigate the "network of networks" scenario, thus passing from Social Networking to Social Internetworking. One of the most interesting attempts in this direction is the Social Internetworking System (hereafter, SIS); it regards the connection of several human networks to form a network of human networks [17, 43]. The strength of SIS resides in the fact that this structure is capable of interconnecting users joining different social networks. In this new scenario, concepts and tools of Social Network Analysis can be adapted to evaluate the main features concerning the interactions between users belonging to the same network or to different networks. This new paradigm aims at guaranteing a trade-off between the autonomy of each network of the SIS and the possibility of increasing power, efficiency and effectiveness, obtained through the interaction of the networks of the SIS. To the best of our knowledge, no architecture similar to SIS has been proposed for networks of things yet.

Ever since node centrality was introduced [11], it has been considered an essential feature to investigate a network and its properties. Indeed, several centrality metrics and different approaches to computing them have been presented and reviewed in the literature [14, 23, 44]. From the viewpoint of interest for this paper, the most interesting idea is proposed in [13]. Here, the author highlights how centrality measures, and the values returned by them, can sometimes provide implicit models for the traffic flow within a network.

As one of the most important centrality measure, betweenness centrality [24] has been the subject of in-depth studies in the literature [16, 18]. Based on its definition, the cost for computing the betweenness centrality of a node is high. For this reason, several heuristic approaches, aiming at providing the closest possible value of the betweenness centrality of a node in a reasonable time, have been proposed in the literature (see [9, 15, 25, 47], to cite a few).

As for the Internet of Things, which is an example of a very dynamic and constantly evolving network, the approaches for the incremental computation of betweenness centrality are extremely interesting. Among these, we mention the ones described in [32, 36, 46]. Specifically, in [32], the authors propose iCENTRAL, which is well suited for large and evolving biconnected graphs. In [46], the authors illustrate an approach for a quick incremental computation of betweenness centrality. After a pre-processing phase, the computational cost of this approach is independent from the network size. In [36], the authors describe an approach that reduces the search space by finding a set of candidate nodes that are the only ones to be updated during the incremental computation of the betweenness centrality.

Surprisingly, despite the introduction of the SIoT paradigm and the strong tie existing among betweenness centrality and information diffusion, there are very few studies concerning the role of betweenness centrality in IoT. To the best of our knowledge, the only approaches dealing with centrality in IoT have been proposed as part of methods for determining trustworthiness [34, 42] or network navigability [37, 41] in IoT. Anyway, in all these cases, centrality is simply a part of the proposed approaches and not the central topic to investigate. By contrast, in this paper, betweenness centrality is the very goal, and all the results we present here can be applied in many contexts comprising the two mentioned above, along with several other ones.

3 THE PROPOSED PARADIGM

We define a MIE $\mathcal{M}$ as a set of m IoTs. Formally speaking, $\mathcal{M} = \{\mathcal{I}_1, \mathcal{I}_2, \cdots, \mathcal{I}_m\}$, where $\mathcal{I}_k$ is an IoT.

Let o_j be an object of $\mathcal{M}$. We assume that, if o_j belongs to $\mathcal{I}_k$, it has an instance ι_{j_k}, representing it in $\mathcal{I}_k$.

In $\mathcal{M}$, *a set MD_j of metadata* is associated with an object o_j. We define a rich set of metadata of an object, because metadata play a key role in favoring the interoperability of IoTs and their objects, which is the main objective of our paradigm. As a consequence, MD_j consists of three different subsets:

$$MD_j = \langle MD_j^D, MD_j^T, MD_j^O \rangle$$

MD_j^D represents the set of *descriptive metadata*. It denotes the type of o_j. For representing and handling descriptive metadata, a proper taxonomy, such as the one defined by the IPSO Alliance [1], can be adopted.

MD_j^T represents the set of *technical metadata*. It must be compliant with the object type. In other words, there is a different set of metadata for each object type of the taxonomy. Also in this case, the IPSO Alliance provides a well defined set of technical metadata for each object type.

MD_j^O represents the set of *operational metadata*. It regards the behavior of o_j. The operational metadata of an object o_j is defined as the union of the sets of the operational metadata of its instances. Specifically, let $\iota_{j_1}, \iota_{j_2}, \ldots, \iota_{j_l}$, $l \leq m$, be the instances of o_j belonging to the IoTs of $\mathcal{M}$. Then, $MD_j^O = \bigcup_{k=1}^{l} MD_{j_k}^O$. $MD_{j_k}^O$ is the set of the operational metadata of the instance ι_{j_k}. In order to understand the structure of $MD_{j_k}^O$, we first have to analyze the structure of $MD_{jq_k}^O$, i.e. the set of operational metadata between two instances ι_{j_k} and ι_{q_k}, of the objects o_j and o_q, in the IoT $\mathcal{I}_k$. $MD_{jq_k}^O$ is given by the set of metadata associated with the transactions between ι_{j_k} and ι_{q_k}.

Specifically, $MD_{jq_k}^O = \{T_{jq_{k_1}}, T_{jq_{k_2}}, \ldots, T_{jq_{k_v}}\}$, where $T_{jq_{k_t}}$, $1 \leq t \leq v$, represents the metadata of the t-th transaction between ι_{j_k} and ι_{q_k}, assuming that v is the current number of transactions between the two instances. $T_{jq_{k_t}}$ can be represented as:

$$T_{jq_{k_t}} = \langle reason_{jq_{k_t}}, type_{jq_{k_t}}, dest_{jq_{k_t}}, success_{jq_{k_t}}, start_{jq_{k_t}}, finish_{jq_{k_t}} \rangle$$

where:

- $reason_{jq_{k_t}}$ denotes the reason causing the transaction, chosen among a set of default values;
- $type_{jq_{k_t}}$ indicates the transaction type (e.g., unicast, multicast, and so forth);
- $dest_{jq_{k_t}}$ denotes the destination node of $T_{jq_{k_t}}$; this could belong to the network $\mathcal{I}_k$ or not. In this last case, it is necessary to reach it from $\mathcal{I}_k$ through one or more cross nodes, if possible;
- $success_{jq_{k_t}}$ denotes if the transaction succeeded;
- $start_{jq_{k_t}}$ is the timestamp associated with the beginning of the transaction;
- $finish_{jq_{k_t}}$ is the timestamp associated with the end of the transaction (its value is NULL if the transaction failed).

We are now able to define the set of the operational metadata MD_{jk}^O of an instance ι_{j_k} of $\mathcal{I}_k$. Specifically, let $\iota_{1_k}, \iota_{2_k}, \ldots, \iota_{w_k}$ be all the instances belonging to $\mathcal{I}_k$. Then, $MD_{jk}^O = \bigcup_{q=1..w, q\neq j} MD_{jq_k}^O$. In other words, the set of operational metadata of an instance ι_{j_k} is given by the union of the sets of the operational metadata of the transactions between ι_{j_k} and all the other instances of the IoT, which it belongs to.

Given an instance ι_{j_k}, relative to an object o_j and an IoT $\mathcal{I}_k$, we define the metadata MD_{j_k} of ι_{j_k} as:

$$MD_{j_k} = \langle MD_j^D, MD_j^T, MD_{j_k}^O \rangle$$

In other words, the descriptive and the technical metadata of an instance ι_{j_k} coincide with the ones of the corresponding object o_j. Instead, the operational metadata of ι_{j_k} is a subset of the operational metadata of o_j, which comprises only those ones regarding the transactions, which ι_{j_k} is involved in.

It is possible to associate a graph $G_k = \langle N_k, E_k \rangle$ with $\mathcal{I}_k$. N_k indicates the set of the nodes of $\mathcal{I}_k$. There is a node n_{j_k} for each instance ι_{j_k} of an object o_j in $\mathcal{I}_k$. E_k denotes the set of the edges of $\mathcal{I}_k$. There is an edge $e_{jq_k} = (n_{j_k}, n_{q_k})$ if there exists a link between the instances ι_{j_k} and ι_{q_k} of the objects o_j and o_q in the network $\mathcal{I}_k$.

Also the overall MIE $\mathcal{M}$ can be represented as a graph:

$$\mathcal{M} = \langle N, E \rangle$$

Here,

- $N = \bigcup_{k=1}^{m} N_k$;
- $E = E_I \cup E_C$, where:
  - $E_I = \bigcup_{k=1}^{m} E_k$;
  - $E_C = \{(n_{j_k}, n_{j_q}) | n_{j_k} \in N_k, n_{j_q} \in N_q, k \neq q\}$

Observe that n_{j_k} and n_{j_q} are the nodes corresponding to the instances ι_{j_k} and ι_{j_q} of the object o_j in $\mathcal{I}_k$ and $\mathcal{I}_q$.

In other words, a MIE $\mathcal{M}$ can be represented as a graph whose set of nodes is the union of the sets of nodes of the corresponding IoTs. The set E of the edges of $\mathcal{M}$ consists of two subsets E_I and E_C. E_I is the set of the inner edges of $\mathcal{M}$ and is the union of the sets of the edges of the corresponding IoTs. E_C is the set of the cross edges of $\mathcal{M}$; there is a cross edge for each pair of instances of the same object in different IoTs.

We call:

- *i-edge* an edge of $\mathcal{M}$ belonging to E_I;
- *c-edge* an edge of $\mathcal{M}$ belonging to E_C;
- *c-node* a node of $\mathcal{M}$ involved in at least one c-edge;
- *i-node* a node of $\mathcal{M}$ not involved in any c-edge;
- *c-object* an object having at least a pair of instances whose corresponding nodes are linked by a c-edge.

3.1 An example of a MIE

To the best of our knowledge, in the literature there is no known case study or real example about Multi IoTs Environments yet. As a consequence, to provide the reader with an example, and, at the same time, to have a testbed for our experiments, we constructed a MIE starting from some open data about things available on the Internet. In particular, we derived our data from *Thingful* [2]. This is a search engine for the Internet of Things, which allows users to search among a huge number of existing things, distributed all over the world. Thingful also provides some suitable APIs allowing the extraction of all the data we are looking for.

In order to construct our MIE, we decided to work with 250 things whose data was derived from Thingful. Given the huge number of things available in Thingful, it could appear that the number of things composing our testbed is excessively limited. However, we observe that:

- This was the first attempt to construct a real MIE and, then, it was extremely important for us to have a full control of it in order to verify if we were proceeding well. A full human control with a much higher number of nodes would not have been possible.
- We wanted to fully analyze the behavior, the strengths and the weaknesses of our crawler and to understand, step by step, its way of operating vs the ones of other crawlers. Again, a full human verification of these aspects would not have been possible with a larger testbed.
- As it will be clear in the following, our approach to obtaining the testbed is fully scalable. As a consequence, an interested researcher can apply it to construct a much larger testbed, if necessary.

We considered three dimensions of interest for our MIE, namely:

a. *Category*: It specifies the kind of measure performed by a given thing. The categories we have chosen were five, namely *home*, *health*, *energy*, *transport*, and *environment*. Each category originated an IoT. Each thing was assigned to exactly one category.
b. *Coastal distance*: It specifies the coastal distance (i.e., the distance from any sea, lake or river) of each thing. The distance values we have set were: *(i) near*, for things distant less than 20 kilometres from the coast, for the categories *environment* and *energy*, and less than 5 kilometres for the other three categories; *(ii) mid*, for things whose minimum distance from the coast was between 20 and 105 kilometres, for the categories *environment* and *energy*, and between 5 and 25 kilometres for the other three categories; *(iii) far*, for things whose minimum distance from the coast was higher than 105 kilometres, for the categories *environment* and *energy*, and higher than 25 kilometres for the other three categories. An IoT was created for each distance value. The different coastal distance values for *environment* and *energy*, on the one hand, and for the other three categories, on the other hand, have been determined after having analyzed the distribution of the involved categories of things against the coastal distance, in such a way as to produce a uniform distribution of each category of things in the three IoTs related to the coastal distance dimension.
c. *Altitude*: it specifies the altitude of the place where the thing is located. The altitude values we have defined were: *plain* (corresponding to an altitude less than 500 meters), *hill* (corresponding to an altitude between 500 and 1000 meters), and *mountain* (corresponding to an altitude higher than 1000 meters). An IoT was created for each altitude value.

As a consequence, our MIE consists of 11 IoTs. We associated an object with each thing; therefore, we had 250 objects. In principle, for each object, we could have associated an instance for each dimension. However, in order to make our testbed closer to a generic MIE representing a real scenario, where it is not said that all the objects have exactly the same number of instances, we decided to not associate three instances with each object. Instead, we associated only one instance (distributed uniformly at random among the three dimensions and taking into account the features of the things of the IoTs of a given dimension) to 200 of the 250 objects. Analogously, we associated two instances (distributed by following the same guidelines mentioned above) to 35 of the 250 objects. Finally, we associated three instances, one for each possible dimension, to 15 of the 250 objects. At the end of this phase, we had 315 instances, distributed among the 11 IoTs of our MIE as shown in Table 1.

To complete our MIE and its network representation, we had to define a policy to create *i-edges*. In fact, it was clear that our MIE should have had a node for each instance and a c-edge for each pair of instances referring to the same object. Therefore, the last decision regarded how to define i-edges. Given our scenario, it appeared us reasonable to consider distances among things as the leading parameter for the creation of i-edges. To carry out this last task, we have preliminarily computed the distribution of the number of connected components possibly created from our instances against

IoT	*Number of instances*
a.home	22
a.health	22
a.energy	22
a.transport	22
a.environment	22
b.near	14
b.mid	38
b.far	53
c.plain	44
c.hill	50
c.mountain	6

Table 1: Number of instances present in the IoTs of our MIE

the maximum possible distance. Obtained results are reported in Figure 1. Based on this figure, in order to obtain a balanced number of connected components, we decided to connect two instances of the same IoT if the distance of the corresponding things was lesser than 1000 kilometers.

After this last choice, our MIE was fully defined. In order to help the reader to mentally portray it, in Figure 2, we provide a graphical representation. The interested reader can find the corresponding dataset (in the `.csv` format) at the address http://daisy.dii.univpm.it/mie/datasets/mie1/. The password to type is "`za.12&;lq74:#`".

4 REDEFINITION OF THE BETWEENNESS CENTRALITY MEASURE

As pointed out in the Introduction, in order to illustrate how the issues typical of Social Network Analysis can be extended to MIE, in this section, we investigate the case of betweenness centrality measure. Given a node $n_j \in N$ of a network $\mathcal{N}$, the classic definition of betweenness centrality is the following:

$$BC(n_j) = \sum_{n_s \in N, n_t \in N, n_s \neq n_j, n_t \neq n_j} \frac{\sigma_{n_s n_t}(n_j)}{\sigma_{n_s n_t}}$$

where $\sigma_{n_s n_t}$ is the total number of the shortest paths from n_s to n_t, whereas $\sigma_{n_s n_t}(n_j)$ is the number of those shortest paths passing through n_j.

If $\mathcal{N}$ is the network corresponding to a MIE, this formula involves all the shortest paths of all the nodes of the MIE indistinctly. In fact, it does not consider the different IoTs composing the MIE and does not distinguish c-nodes from i-nodes and c-edges from i-edges. We argue that, owing to these weaknesses, BC could present several problems in a MIE context, especially when it is necessary a centrality measure that privileges those nodes allowing the crossing from an IoT to another.

To address the challenges mentioned above, we define two new centrality metrics.

The first of them is called *Inner Betweenness Centrality* (IBC, for short) and is defined as follows.

Let $n_{j_k} \in N_k$ be the node corresponding to the instance ι_{j_k} of the object o_j in the IoT $\mathcal{I}_k$ of the MIE $\mathcal{M}$. The Inner Betweenness Centrality $IBC(n_{j_k})$ is defined as:

$$IBC(n_{j_k}) = \sum_{n_{s_k} \in N_k, n_{t_k} \in N_k, n_{s_k} \neq n_{j_k}, n_{t_k} \neq n_{j_k}} \frac{\sigma_{n_{s_k} n_{t_k}}(n_{j_k})}{\sigma_{n_{s_k} n_{t_k}}}$$

In few words, $IBC(n_{j_k})$ computes the betweenness centrality of a node by selecting only the minimum paths between the nodes belonging to the IoT which n_{j_k} belongs to.

IBC can be considered as an evolution of BC, capable of evaluating inner central nodes, i.e., those nodes being central (in the betweenness centrality sense) for the other nodes of the network they belong to (in this formula, this is evidenced by the fact that both the source and the target nodes belong to the same network N_k).

The second betweenness centrality measure that we propose in this paper is called *Cross Betweenness Centrality* (CBC, for short) and is defined as follows. Let $n_{j_k} \in N_k$ be the node corresponding to the instance ι_{j_k} of the object o_j in the IoT $\mathcal{I}_k$. The Cross Betweenness Centrality $CBC(n_{j_k})$ is defined as:

$$CBC(n_{j_k}) = \sum_{n_{s_u} \in N_u, n_{t_v} \in N_v, u \neq v} \frac{\sigma_{n_{s_u} n_{t_v}}(n_{j_k})}{\sigma_{n_{s_u} n_{t_v}}}$$

In few words, $CBC(n_{j_k})$ computes the centrality of a node by selecting only the minimum paths between nodes belonging to different networks. There is no constraint on the node n_{j_k} of which we are computing the CBC. As a matter of fact, n_{j_k} could belong either to N_u or to N_v or, finally, to another IoT of the MIE different from N_u and N_v.

CBC can be considered as an evolution of BC capable of detecting central (in the betweenness centrality sense) c-nodes.

IBC and CBC are capable of overcoming the limits characterizing the classic BC in a MIE. Indeed, the main problem of BC is the lack of distinction between c-nodes and i-nodes so that, after having found that the value of BC is high for a given node, we cannot say if this node is central for a single IoT or for the MIE.

If we want to know the most central (in the betweenness centrality sense) nodes in a single network, the most suitable choice is IBC, because this measure considers only i-nodes, which are the nodes we are looking for. Thus, we are able to analyze a single IoT of the MIE and to perform a local detection of central nodes. Given the complexity of a MIE, such a specific study can be really useful for several applications.

By contrast, if we want to know the most central c-nodes in a MIE, the most suitable choice is CBC. Indeed, dually to IBC, CBC ignores i-nodes and focuses on c-nodes. This implies that this measure is capable of evidencing the most suitable nodes allowing the cooperation of nodes belonging to different IoTs.

4.1 Tests

In this section, we describe the tests that we carried out to evaluate the significance of our new betweenness centrality measures in a MIE and to compare them with the classical betweenness centrality. In our test activity, we adopted the testbed illustrated in Section 3.1.

We started our experiments considering the top-12 central nodes returned by BC and verifying the rank of the same nodes when the other centrality measures are applied[1]. Obtained results are reported in Table 2.

[1]Recall that our MIE consists of 315 nodes.

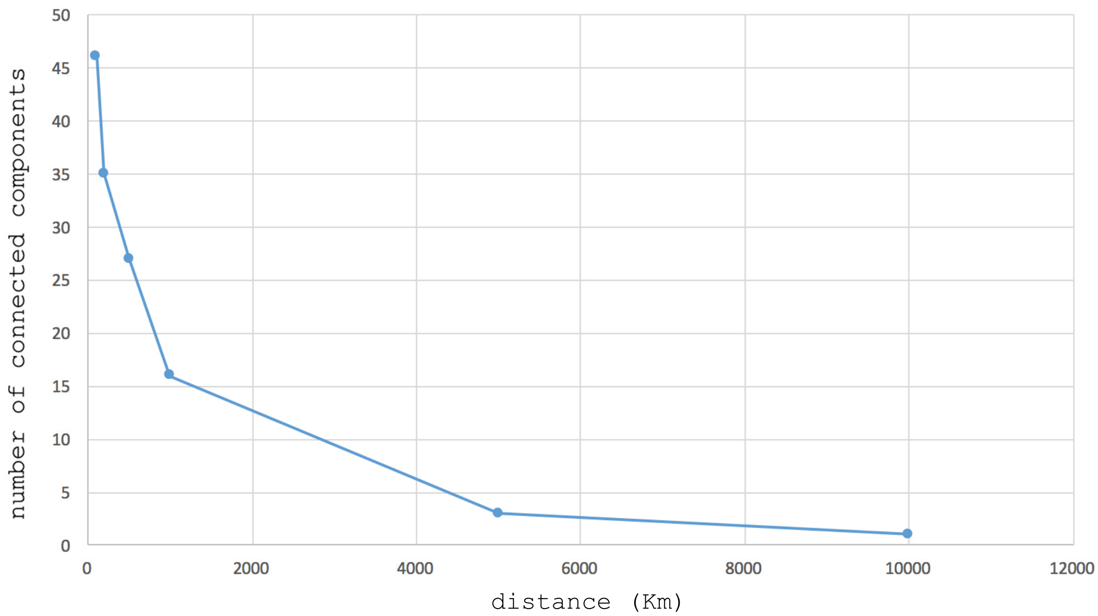

Figure 1: Distribution of the number of connected components of the instances of our MIE against the maximum possible distance

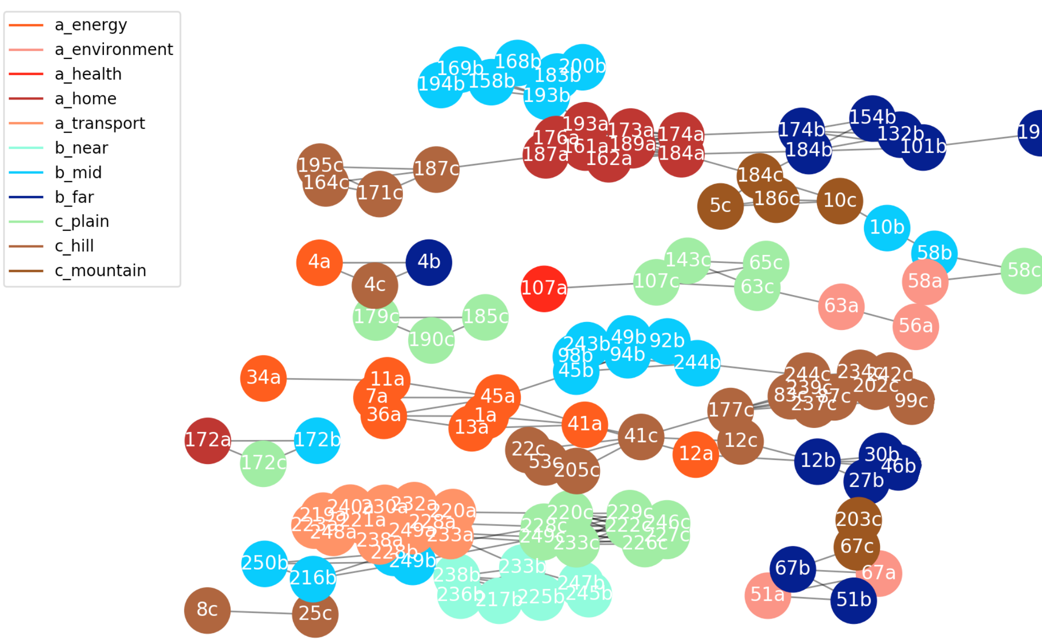

Figure 2: Graphical representation of our MIE

From the analysis of this table we can clearly observe that BC and IBC return completely different results. In fact, 11 of the top-12 central nodes returned by BC have a rank higher than 200 in IBC. Instead, a good correspondence can be observed between the ranks of BC and CBC, denoting that BC shows a good capability of finding the most “soft” central nodes in a MIE.

Then, we repeated the same evaluation for the top-12 central nodes returned by IBC. Obtained results are reported in Table 3.

Nodes	*BC rank*	*IBC rank*	*CBC rank*
76b	1	208	1
76c	2	207	2
99b	3	202	3
99c	4	201	4
54b	5	2	158
12b	6	293	5
76a	7	209	6
41a	8	232	7
244c	9	245	8
244b	10	246	9
149c	11	288	10
12a	12	294	11

Table 2: IBC and CBC ranking of the top-12 central nodes returned by BC

Nodes	*IBC rank*	*BC rank*	*CBC rank*
177c	1	37	248
54b	2	5	158
57b	3	55	156
33c	4	72	173
21c	5	74	208
211a	6	29	216
133c	7	76	289
91a	8	63	124
212c	9	65	215
156b	10	82	267
144c	11	94	277
142c	12	95	279

Table 3: BC and CBC ranking of the top-12 central nodes returned by IBC

Nodes	*CBC rank*	*BC rank*	*IBC rank*
76b	1	1	208
76c	2	2	207
99b	3	3	202
99c	4	4	201
12b	5	6	293
76a	6	7	209
41a	7	8	232
244c	8	9	245
244b	9	10	246
149c	10	11	288
12a	11	12	294
40c	12	13	233

Table 4: BC and IBC ranking of the top-12 central nodes returned by CBC

From the analysis of this table we can observe that the ranks returned by IBC, on the one hand, and CBC, on the other hand, are totally different. Actually, this was an expected result. However, it is interesting to observe that there is a weak correspondence between IBC and BC, because the top-12 central nodes returned by IBC have a rank between 5 and 95 in BC.

After this, we analyzed the top-12 central nodes returned by CBC. Obtained results are reported in Table 4. Again, we observe a good correspondence between CBC and BC and a totally different behaviors characterizing CBC and IBC.

5 CONCLUSION

In this paper, we have presented a new paradigm, aimed to introduce some ideas typical of Social Internetworking Systems in IoT. We have seen that a MIE can be considered as a set of things connected to each other by means of several kinds of relationship not defined a priori. At the same time, it can be seen as a set of correlated IoTs, one for each kinds of relationship existing among things.

We have also seen that the classical notion of betweenness centrality, which is well suited for a unique IoT, could present some weaknesses in this new scenario, because it is incapable of distinguishing between c-nodes and i-nodes. After this, we have introduced new betweenness centrality measures and we have discussed their features w.r.t. the classic betweenness centrality. Finally, we have presented some experiments devoted to test if our intuition about the inadequacy of the classical betweenness centrality for a MIE was correct and, then, to show the adequacy of the new measures.

In our opinion, this paper is not to be intended as an ending point. By contrast, it is a starting point for addressing many challenges in the context of IoT, based on the ideas to adopt Social Internetworking, instead of the much simpler Social Networking paradigm. For instance, analogously for what we have done for betweenness centrality, we plan to investigate new forms of centralities specifically suited for a MIE. Furthermore, we plan to investigate ecosystems in MIEs. An ecosystem must be intended as a virtual IoT constructed starting from the real ones by selecting nodes from different IoTs and by linking them through a specific new relationship of interest. Finally, it would be extremely interesting to investigate trustworthiness and reputation in a MIE. Again, we argue that the classical metrics and approaches for measuring these parameters in a unique IoT are not adequate in the new context, and new definitions of them, based on c-nodes and c-edges, are in order.

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