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Energy Awareness and the Role of "Critical Mass" In Smart Cities

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Abstract:- A Smart City could be depicted as a place, logical and physical, in which a crowd of heterogeneous entities is related in time and space through different types of interactions. Any type of entity, whether it is a device or a person, clustered in communities, becomes a source of context-based data.
Energy awareness is able to drive the process of bringing our society to limit energy waste and to optimize usage of available resources, causing a strong environmental and social impact. Then, following social network analysis methodologies related to the dynamics of complex systems, it is possible to find out, emergent and sometimes hidden new habits of electricity usage. Through an initial Critical Mass, involving a multitude of consumers, each related to more contexts, we evaluate the triggering and spreading of a collective attitude. To this aim, in this paper, we propose a novel analytical model defining a new concept of critical mass, which includes centrality measures both in a single layer and in a multilayer social network.

Keywords:- Critical Mass, Energy Awareness, Multilayer Networks, Smart City, Social Network Analysis.

I. INTRODUCTION

In a Smart City, each entity is a source node that provides data about city context and social dynamics. The term "Smart City" indicates a coordinated set of planned Information and Communication Technologies (ICTs) interventions, able to make the city sustainable in terms of quality and management, referred to some topics such as energy, environment, urban life and services, socio-economic aspects, mobility, government, social quality of life.

The size of cities plays a crucial role in more socio-economic activities. In particular, there is a strong relation between the city size and human interactions. The total number of contacts and communication activities grows superlinearly as the city population grows [1]. Starting from a minimum number of nodes, referred as Critical Mass, it is possible to start and foster a process that will lead them to cluster, following a metric of similarity and an approach based on the identification of the central geographical location (location-based).

Energy consumption habits strictly depend on technology, individual and social attitude to exchange information about them [2]: "knowledge" is the foundation of the smart city. Therefore, the question is what type of channel or tool a consumer should use to make the city "smart"? Which application could encourage energy saving? One possible option could be an application encouraging a more conscious employment of energy through social interactions [3]. The location-based approach also allows mapping a geo-contextualized energy awareness within the network. In this scenario, entities will be able to compare and disseminate data about its own consumption habits, triggering an overall reduction of consumptions and causing a strong socio-economic impact.

Social phenomena and dynamics influence people relationships, decisions and, consequently, their actions. Interactions among entities, achieved via multiple patterns (or layers) [4], could be studied using paradigms and analytical tools derived from behavioural sciences [5]. This multilayer framework allows a deep understanding of the importance of relationships strength within the population [6]. Users are increasingly keen to interact, cooperate and collaborate, share contents, and to participate through social media. The role of a single actor or a group of people, community or coalition, could contribute to trigger dynamics inside population [7], [8].

The paper is organized as follows: in section II we explain the related work and background, in section III we propose a new model to evaluate a new kind of critical mass. Finally, section IV consists of conclusion and future works.

II. RELATED WORK AND BACKGROUND

It is well known that for domestic customers the possibility to get real-time information about energy consumption, thanks to the Smart Metering infrastructure capabilities, does not represent uniquely a sufficient incentive to raise awareness towards energy savings. In fact, the initial interest wears off after a short time. Only such information does not lead to significant improvements in terms of energy savings, since people can appreciate the initial message but, in most cases, this information does not produce any significant long-term effects on energy savings [9]. From this point of view the analysis and implementation of a social-based system, enabling typical mechanisms of information sharing and competition, may conduce to a greater involvement and a better awareness of users regarding efficiency issues [10], [11], [12], [13].

Since diverse phenomena can spread within social networks [14], [15], social network analysis is useful to further investigate network phenomena, which appear relevant to understand hidden dynamics. This kind of analysis considers social relationships in terms of network theory, with nodes, representing the individual actors, and ties (links, edges or connections) which are the relationships between individuals. The resulting structures are complex graphs connecting social contacts, and the graph theory, from a structural point of view, is able to describe these relationships using metrics, such as centrality measures, clustering coefficient, etc. The community detection is one of the most well-known structural problems in the social network context. Individual's actions have to be evaluated not in isolation [16], rather we must consider the connections with others, seen as players, in order to favour the social contagion processes [17].

Through this analysis, human social networks may exhibit interpersonal influence with respect to several different phenomena of great interest in a population such as diseases, smoking, habits, happiness, etc.

A social network can be described as a set of people interacting each other through some types of pattern. Generally, the relationships between entities on a network are considered at the same layer. However, in a real context, different and not mutually exclusive relationships within the community should be taken into account, that is, interdependencies and relationships involve different levels. This concept introduces a new point of view of the social network analysis: the nodes and their relationships must be considered and weighed on different contexts (or layers). Moreover, the weight of their decisions and their behaviours has an impact on many different levels. Network science has been largely successful in abstracting meaning from single-layer subsystems, but it is only recently that multilayer networks [4] have become a popular paradigm to model interrelated subsystems and entire systems. This is mainly due to the capability of multilayer models for understanding the bigger entity more realistically. The real prospective of multilayer networks has not been exploited yet. Large group problems can be solved by a Critical Mass (CM) [7], defined as a minimum number of initial contributors, which has the power to involve the rest of population, for example, persuading the remaining members of the population towards the adoption of a specific behaviour. The dynamics of initiating CM depends on actor's decision and on incentives for adopting a well-defined behaviour [8]. Because of group heterogeneity, all individuals within the system could tend to different behaviours. The concept of similarity is important in the dynamics of collective action and Critical Mass mobilization. Humans tend to interact and create groups with other humans who have similar features or interests [18]. The study of CM and its ability to involve the rest of the population, producing a phenomenon known as *Bandwagon Effect*, allows evaluating how an attitude can spread throughout the network. In order to pursue and disseminate a public good (e.g. energy awareness), we have to address the issues of the induction of interpersonal influence, similarity and diversity degree among individuals.

III. MATERIALS AND METHODS

A Smart City is a complex system involving several issues and challenges, thus reducing the analysis to a single layer model does not allow capturing the dynamics of this multitude of nodes and edges. For this reason, we need a multilayer paradigm. It allows taking into account simultaneously the huge number of contexts, somehow related each other, and investigating the complex dynamics generated by the inter-layer and intra-layer interactions between entities in the different layers. A city can be seen as a large social networks or an agglomeration of social links.

In the Smart City context, infrastructure, both in time and space, plays a fundamental role in enabling social interactions [19]. We can now represent the city as collection of interconnected entities, either nodes or communities, interacting each other in a multi-layer network with cognitive and self-organization capabilities (Fig. 1). The CM is represented by the minimum number of people which actively join the action and start the diffusion process, sharing information related to their energy consumption etc., in order to influence a collective behaviour. It can trigger social dynamics and phenomena, such as social contagion [17], through similarity-based interactions. Thus, the network increasingly changes, strengthening the influence and, finally, spreading a "good behaviour" (e.g. energy saving).

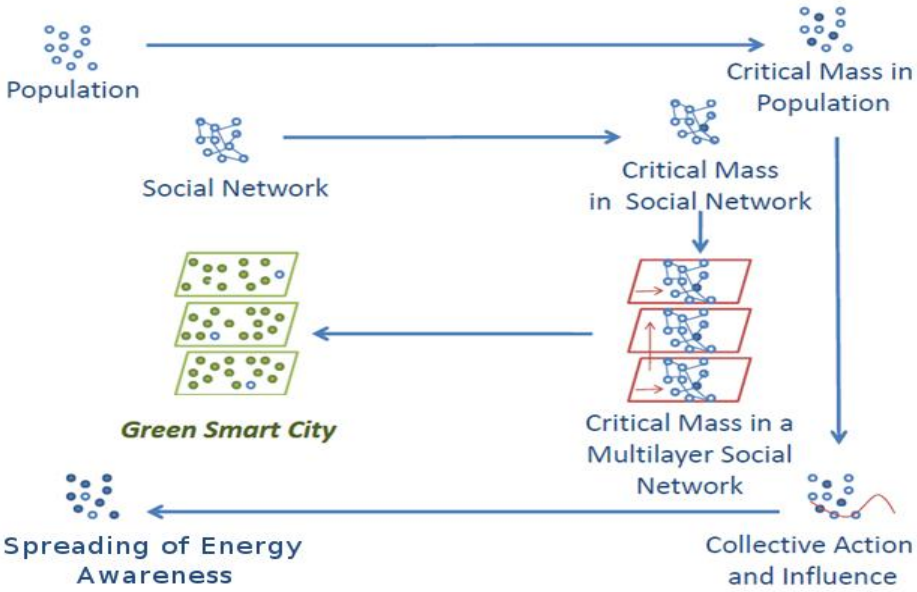

Fig. 1. Spreading energy awareness in a Multilayer Smart City.

CM is defined as the minimum coalition n, such that if actors organize into coalitions of size n, at least n people will prefer mutual cooperation to unilateral defection [7], and it is calculated as it follows:

$$\min(n) \; s.t. \left\{ \sum_{i=1}^{N} H(R_i - T_i) \right\} \geq n \tag{1}$$

where N is the overall population and $min(n)$ is the minimum coalition size.

CM depends also on the Heaviside function of the difference between Reward and Temptation payoffs, R_i and T_i respectively, evaluated considering different types of games in which a player is a randomly selected node from the population.

In this work, we extend the concept of critical mass introducing a social network approach. Thus, CM is transformed into a value that depends on the network structure and, in particular, it is calculated considering the eigenvector centrality measure [20]. In our analysis, the eigenvector centrality allows including the concept of influence. It can also be seen as a weighted sum of not only direct connections, but also indirect connections of every length [21]. Eigenvector centrality, starting from the spectral properties of the adjacency matrix, considers not only the number of links of each node and the quality of such connections as well. Central nodes are the most influential nodes, which can condition the behaviours of their neighbourhood. Considering the eigenvector centrality in our model, the critical mass becomes:

$$\min(n^*) \; s.t. \left\{ \sum_{i=1}^{N} H(R_i - T_i)\, H(x_i - \mu) \right\} \geq n^* \tag{2}$$

where $min(n^*)$ is calculated introducing a second Heaviside function of the difference between the eigenvector centrality measure x_i of each node and the mean value μ of eigenvector centralities. This leads to decrease the critical mass value. In fact, exploiting the central nodes, the spreading of a social phenomenon becomes more efficient and quick, as central nodes are the more connected nodes. Then, the analysis of critical mass is further extended considering a multilayer approach, taking a different eigenvector-like centrality measure in each layer α in order to consider different degrees of importance (or influence) in different layers of the network. Thus, to calculate the centrality of a node within a specific layer, one must take into account all the other layers, as it may depends not only on the neighbours that are linked to x_α within that layer, but also on all other neighbours of

x_α that belong to other layers. In other words, one needs to consider the situation where the influence amongst layers is heterogeneous. To this purpose, one can introduce an influence matrix W, defined as a non-negative matrix, such that $w_{\alpha\beta}$ measures the influence on a layer α given by the layer β. Given a multiplex network M and an influence matrix $W = (w_{\alpha\beta})$, the global heterogeneous eigenvector-like centrality of M is defined as it follows:

$$\min(n^{**})\ s.t. \left\{ \sum_{i=1}^{N} H(R_i - T_i)\, H(\lambda_i - \bar{\lambda}) \right\} \geq n^{**} \tag{3}$$

where $min(n^{**})$ is calculated introducing a Heaviside function of the difference between λ_i , the eigenvalues of the matrix obtained calculating the Khatri-Rao product of the matrices of influence and of the multilayer [4] and $\bar{\lambda}$ the threshold chosen as the average of these values. The analysis of the critical mass in the multilayer structure allows including the tie's strength. In fact, the more layers are utilized, the stronger the tie between two individuals, so the number of layers in the multilayer is an indicator of the tie's strength, in particular [22]:

$$m\,\omega_{ij} = \sum_{\alpha=1}^{M} \frac{a_{ij}^{\alpha}}{M} \tag{4}$$

where M is the total number of layers in the multiplex, m is the number of layers in which the two nodes interact, a_{ij} is an element of the adjacency matrix (it is equal to 1 if i and j are connected, otherwise 0), and ω_{ij} is the influence between the two nodes i and j. Furthermore, as underlined in [23], the multilayer structure is able to give rise to a super-diffusive process, thus speeding up the diffusion process, making it faster than that occurring within each of the layers. Thus, we introduce a multilayer analysis in order to consider the diffusion dynamics in the multilayer structure and see how it influences the critical mass value.

We have simulated the critical mass against the population, and in Fig. 2 we illustrate the three curves corresponding to the three values of critical mass, $min(n)$, calculated according to (1), $min(n^{*})$, according to (2), and $min(n^{**})$, according to (3) considering a two-layer structure with a strong influence between the two layers. We observe that the critical mass values, evaluated introducing the centrality measures in the single layer, plotted in the red curve, are lower than the values obtained considering equation (1), where no centrality measure is taken into account. Extending the analysis to the multilayer network, as we see in the "green" curve, we can note a further reduction in the critical mass.

This finding suggest that, including the measures of centrality both in the single-layer and in the multilayer structures, we are able to obtain a CM lower than in (1). This is related to address also the structural properties of the network, as the measure of centrality allows weighing the network nodes in a different way, so that central nodes have the capability to influence strongly the neighbourhood and, consequently, the whole network [17]. This is even more marked in the multilayer structure since, as said before, it is able to increase the tie's strength between two nodes. In a multilayer perspective, central nodes increment their weight in the network, lowering the number of central nodes needed to give a boost to the diffusion process.

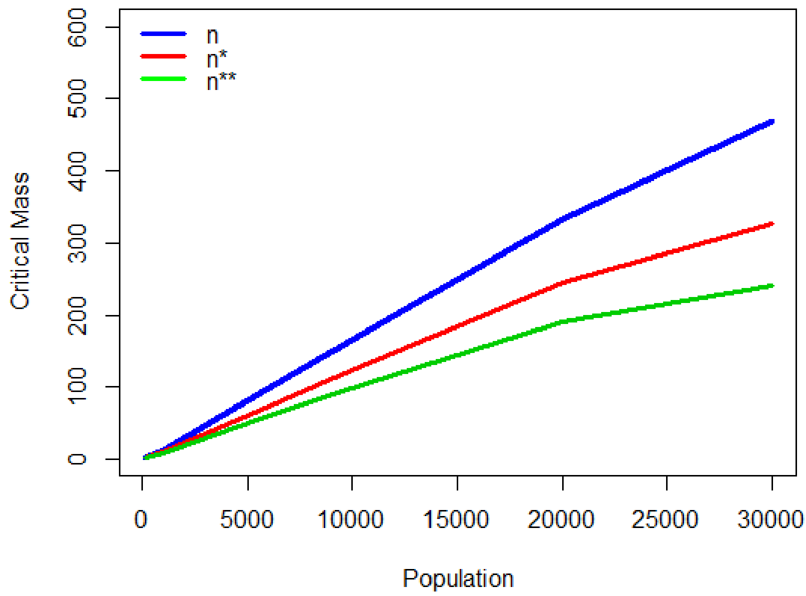

Fig. 2. Critical Mass versus population.

IV. CONCLUSION

ICT can provide methodologies and innovative approaches to analyse issues and challenges of Smart City, joining synergically data, entities and services in a complex multilayer approach. Social network analysis becomes an essential analytical tool used to understand how highly connected systems and entities which form social ties, weak and strong relationships inside and outside groups and clusters, operate. Following complex networks theory and exploiting the increasing availability of big data [24], one of the major efforts of modern theory of complex systems is to find a suitable representation able to extract complex structural and dynamical properties of networks.

Following social network analysis methodologies related to the dynamics of complex systems, it is possible to find out emergent behaviours, targeted at energy saving. Through an initial Critical Mass, it is possible to evaluate how to trigger and spread a collective attitude involving a multitude of consumers. To this aim, in this paper, we have proposed a novel analytical model defining a new concept of critical mass, which includes centrality measures both in a single layer and in a multilayer social network. Our simulation results show how the interplay among entities in the different layers, together with the centrality measure, permits to lower the Critical Mass size able to trigger and spread the diffusion of good consumers' habits inside the Smart City.

In the future, our efforts will be focused on finding out the satisficing level of similarity between entities, which maximizes, in time and space, the spreading of social attitudes, and we will apply this study to various types of social network structures.

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REFERENCES

[1]. Schläpfer, M., Bettencourt, L. M., Grauwin, S., Raschke, M., Claxton, R., Smoreda, Z., West, Geoffrey, B., Ratti, C. (2014). The scaling of human interactions with city size. *Journal of The Royal Society Interface*, 11(98), 20130789.

[2]. Khansari, N.; Darabi, H. R.; Mansouri, M.; and Mostashari, A. (2015). Case study of energy behavior: Systems thinking approach. *In Systems Conference (SysCon), 2015 9th Annual IEEE International*, 373–376. IEEE.

[3]. De Luca, V., & Castri, R. (2014). The social power game: A smart application for sharing energy-saving behaviours in the city. *FSEA 2014*, 27.

[4]. Boccaletti, S., Bianconi, G., Criado, R., Del Genio, C. I., Gómez-Gardeñes, J., Romance, M., Sendina-Nadal, I., Wang, Z., Zanin, M. (2014). The structure and dynamics of multilayer networks. *Physics Reports*, 544(1), 1-122.

[5]. Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications (Vol. 8). Cambridge university press.

[6]. Granovetter, M. (1983). The strength of weak ties: A network theory revisited. *Sociological theory*, 1(1), 201-233.

[7]. Centola, D. M. (2013). Homophily, networks, and critical mass: Solving the start-up problem in large group collective action. *Rationality and society*, 25(1), 3-40.

[8]. Heckathorn, D. D. (1996). The dynamics and dilemmas of collective action. *American Sociological Review*, 250-277.

[9]. Darby, S. (2006). The effectiveness of feedback on energy consumption. A Review for DEFRA of the Literature on Metering, Billing and direct Displays, 486, 2006.

[10]. Petersen, J. E., Shunturov, V., Janda, K., Platt, G., & Weinberger, K. (2007). Dormitory residents reduce electricity consumption when exposed to real-time visual feedback and incentives. *International Journal of Sustainability in Higher Education*, 8(1), 16-33.

[11]. Schwanzer, M., & Fensel, A. (2010). Energy consumption information services for smart home inhabitants. In *Future Internet-FIS 2010* (pp. 78-87). Springer Berlin Heidelberg.

[12]. Loock, C. M., Landwehr, J. R., Staake, T., Fleisch, E., & Pentland, A. S. (2012). The influence of reference frame and population density on the effectiveness of social normative feedback on electricity consumption, *Thirty Third International Conference on Information Systems*, Orlando USA.

[13]. Skopik, F., & Wagner, C. (2012, July). Novel energy saving opportunities in smart grids using a secure social networking layer. In *Computer Software and Applications Conference (COMPSAC), 2012 IEEE 36th Annual* (pp. 557-566). IEEE.

[14]. Newman, M. E. (2003). The structure and function of complex networks. *SIAM review*, 45(2), 167-256.

[15]. Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world'networks. *nature*, 393(6684), 440-442.

[16]. Easley, D., & Kleinberg, J. (2010). Networks, crowds, and markets: Reasoning about a highly connected world. Cambridge University Press.

[17]. Christakis, N. A., & Fowler, J. H. (2013). Social contagion theory: examining dynamic social networks and human behavior. *Statistics in medicine*, 32(4), 556-577.

[18]. Fowler, J. H., Settle, J. E., & Christakis, N. A. (2011). Correlated genotypes in friendship networks. *Proceedings of the National Academy of Sciences*, 108(5), 1993-1997.

[19]. Bettencourt, L. M. (2013). The kind of problem a city is. *Die Stadt Entschlusseln: Wie Echtzeitdaten Den Urbanismus Verandern: Wie Echtzeitdaten den Urbanismus verändern*, 175-187.

[20]. Bonacich, P., & Lloyd, P. (2001). Eigenvector-like measures of centrality for asymmetric relations. *Social Networks*, 23(3), 191-201.

[21]. Bonacich, P. (1987). Power and centrality: A family of measures. *American journal of sociology*, 1170-1182.

[22]. Hristova, D., Musolesi, M., & Mascolo, C. (2014). Keep your friends close and your Facebook friends closer: a multiplex network approach to the analysis of offline and online social ties. *arXiv preprint arXiv*:1403.8034.

[23]. Gomez, S., Diaz-Guilera, A., Gomez-Gardeñes, J., Perez-Vicente, C. J., Moreno, Y., & Arenas, A. (2013). Diffusion dynamics on multiplex networks. *Physical review letters*, 110(2), 028701.

[24]. Tan, W., Blake, M.B. Saleh, I., Dustdar, S. Social-Network-Sourced Big Data Analytics. *IEEE Internet Computing* (5), 62-69 (2013).