Technological Forecasting & Social Change 142 (2019) 42–55

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

A Multiple-Attribute Decision Making-based approach for smart city rankings design

Soledad Escolar[a,*], Félix J. Villanueva[a], Maria J. Santofimia[a], David Villa[a], Xavier del Toro[b], Juan Carlos López[a]

[a] *School of Computing Science, University of Castilla-La Mancha, Ciudad Real, Spain*
[b] *The Energy Research and Industrial Applications Institute (INEI), University of Castilla-La Mancha, Ciudad Real, Spain*

ARTICLE INFO

Keywords:
Smart cities
Internet of Things
City rankings
City indicators
Information and Communication Technologies

ABSTRACT

Rankings are a valuable element for city-comparison purposes since results withdrawn from these comparisons can, eventually, support the evaluation of strategic decisions taken by cities. Smart city rankings are not an exception and, as they draw more attention, the number of them exponentially increases. This paper evaluates the appropriateness of existing smart city rankings for quantifying the materialization degree of the smart city concept. The analysis reveals that current rankings generally overlook indicators of the Information and Communication Technologies dimension. To bridge this gap, this work proposes a methodology based on Multiple-Attribute Decision Making that uses technological criteria for designing smart city rankings. The proposed methodology is evaluated against the cities of New York, Seoul, and Santander. Imbalances between results provided by the studied rankings and our evaluation are detected, which suggests the need for a new insight into more suitable and precise evaluation of the *smartness* degree of cities.

1. Introduction

Despite that no agreement exists on the definition of smart city (de Santis et al., 2014; Nam and Pardo, 2011a; Yin et al., 2015; Nam and Pardo, 2011b), it is commonly accepted that the term suggests taking advantage of Information and Communication Technologies (ICT) to provide a sustainable economical growth able to increase the quality of life of citizens. *Smart city* refers to a city that monitors and integrates conditions of its critical infrastructures, e.g. roads, bridges, tunnels, rail/subways, airports, seaports, communications, to better optimize its resources, plan its maintenance activities, and monitor security aspects while the services to its citizens are maximized (I. of Things European Research Cluster, 2015). The concept is nowadays linked to Internet of Things (IoT), a term coined in 1999 following the appearance of the smart city term, by Ashton (2009); IoT is defined as the capability to *empower computers with their own means of gathering information, so they can see, hear and smell the world for themselves*. Thus, IoT is transforming how we experience the city by means of a mass of pervasive, hyper-connected *things* at any-time, any-place, with any-other-thing and any-one, using ideally any-path and network. It is estimated that IoT will become the largest device market in the world: the number of *things* will reach more than double the sum of smartphones, PCs, tablets, connected cars, and wearable devices by 2019 B. Insider (2014), which will bring as a result 1.7 trillion in value added to the global economy. Specifically for smart city solutions, the market will achieve 408 billion by 2020 (D. for Business Innovation, Skills, 2013), which means 24% of the IoT global market.

A city has been traditionally considered as a system in equilibrium (Batty, 2013). To become *smart*, a city arranges the adequate resources along one or several key dimensions (e.g. smart parking, structural health, smart lighting, waste management, intelligent transportation systems) to enable added-value services for citizens. Such a transformation requires an intensive usage of those things that *see, hear, and smell the world for themselves* and that are implicitly working for us (Weiser and Brown, 1996). According to Clarke (2015), to be labeled as *smart*, a city just needs to develop a smart city initiative. However, it is generally overlooked to *what* extent these initiatives are smart and how the ICT employed help to achieve their goals. There exist no requirements on the minimum quantity of ICT resources employed to implement a smart initiative (in terms of, for instance, number of things, coverage, services offered to citizens) which, therefore, could be completely uncoupled from this aspect. Beyond the scale, the meaning of *smartness* in a real deployment is unspecific, which wrongly creates the notion that just the usage of ICT becomes a city smart. Some examples

* Corresponding author.
E-mail address: soledad.escolar@uclm.es (S. Escolar).

https://doi.org/10.1016/j.techfore.2018.07.024
Received 21 December 2017; Received in revised form 28 May 2018; Accepted 14 July 2018
Available online 20 July 2018

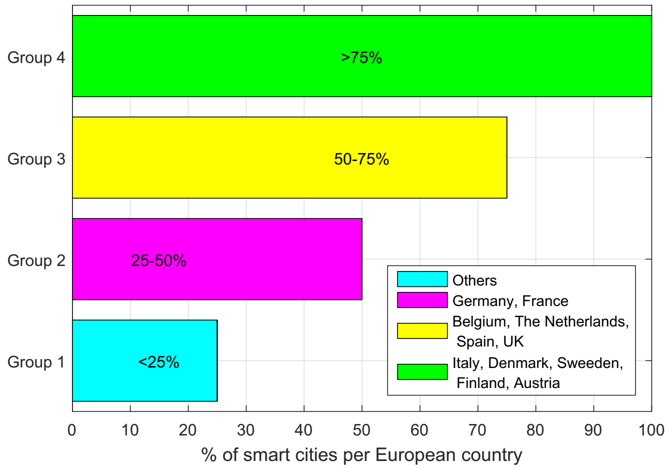

Fig. 1. European cities with at least one smart city initiative.

of initiatives considered smart are: provision of wireless broadband connectivity, grants to replace contaminant cars, LEDs to replace bubbles in lampposts, or more kilometers of bike lanes. Fig. 1 shows the percentage of European cities that have launched at least one smart city initiative. Only 28% of the cities labeled as *smart* in Europe, which represent 51% of the 468 cities with a population over 100,000, have actually fully launched a smart city initiative (Clarke, 2015).

Rankings provide an effective instrument to evaluate the degree of urban development of the cities with regard to a set of indicators related to various urban dimensions (Giffinger and Gudrun, 2010). By comparing the strengths and weakness of cities, a clear learning effect that promotes competition and innovation is generated. However, to be able to effectively rank smart cities, rankings should necessarily include technological criteria in addition to urban criteria, since smart cities rely on ICT for their realization. While some works are investigating the set of KPI (Key Performance Indicators) that enable to quantify the smartness degree of a city (Hara et al., 2016; ITU-T, 2015), other works (e.g. the rankings reviewed in Section 2.2 and Cavada et al., 2014; Jucevicius et al., 2014; Shi et al., 2018), either overlook or do not draw enough attention to the technological dimension of the cities. Consequently, although their results measure the urban development they could fail in reflecting precisely the materialization level of the so-called smart cities.

This paper describes a methodological approach for developing smart city rankings based on technological and smartness criteria. To the best of our knowledge, there is no other research work that investigates smart cities under this perspective. To this aim, Section 2 analyzes the appropriateness of the current rankings as classification method for smart cities. In Section 3 we describe the proposed methodology, the quantification method, dimensions and indicators. Section 4 presents the results of applying our methodology to three smart cities around the world: New York, Santander, and Seoul, and Section 5 presents the discussion of the major outcomes of this analysis. Finally, Section 6 outlines the conclusions and directions for further research.

2. Related work

In the following subsections, we first describe the ranking calculation methods; then, we analyze several city rankings currently used for smart cities classification and, finally, we discuss their suitability to classify smart cities.

2.1. Multiple-Attribute Decision Making

Multiple-Attribute Decision Making (MADM) (Figueira et al., 2005) is a discipline of operations research aimed at scoring and ranking multiple alternatives that are characterized by multiple, usually conflicting attributes. According to the classification done in Hwang and Yoon (1981), MADM corresponds to one of the two branches of Multiple-Criteria Decision Making, which classifies the real-world problems as continuous or discrete, and where MADM focuses on evaluating discrete problems, with a limited number of alternatives that cannot be measured in a single dimension.

The MADM process requires to identify the objectives to be able to make good decisions, to identify the distinct attributes or criteria that will be used to compare alternatives, and to specify a method formal to determine what is the contribution of each alternative to a certain attribute. MADM appears in the 1960s, but still today is a very active field of research (Zavadskas et al., 2014; Pirdashti et al., 2011). For the sake of brevity, in this subsection we focus on reviewing MADM methods based on its methodological approach.

2.1.1. Theoretical foundation

An MADM problem is represented as a matrix. This matrix is called decision matrix and it describes the contribution of each alternative against each attribute. Formally speaking, a decision matrix is denoted as $D = A \times B$, where $A = \{a_1, a_2, \ldots, a_n\}$ is the set of alternatives and $B = \{b_1, b_2, \ldots, b_m\}$ is the set of attributes. Thus, d_{ij} represents the contribution of a_i to the attribute b_j, with $i \in [1,n], j \in [1,m]$. To compute D two operations are generally applied: scoring and weighting. The former involves assigning a numerical value to each d_{ij}, within a preference scale. Attributes may be *benefit attributes*, where higher d_{ij} represents a higher contribution; or *cost attributes*, where lower d_{ij} represents a higher contribution. Weighting involves determining a weight w_j to be the relative importance on attribute b_j, with $\sum_{j=1}^{m} w_j = 1$. To estimate the weights, an MADM method generally provides an explicit weighting system for the different criteria. Note, however, that both operations (scoring and weighting) are not exempt from a certain subjectivity, which is one of the main criticism done to MADM approach.

2.1.2. MADM methods

An MADM method provides a mathematical framework to compute the elements of the matrix D. According to their methodology (Ervural and Kabak, 2015), MADM methods are classified into the following:

Non-compensatory methods do not enable trade-offs between attributes, i.e. the superiority in some attribute cannot compensate the inferiority of some other attribute. The most simple method in this category is the search of the dominant alternative, which is the one that performs at least as well as another on all criteria and strictly better than the others on at least one criterion. Conjunctive and disjunctive methods are based on the idea of introducing thresholds for some attributes, by enabling these attributes may be prioritized against others without thresholds. If the maximum threshold (conjunctive model) is exceeded or the minimum threshold (disjunctive model) is not achieved, the alternative is eliminated of the matrix.

Value-based methods are compensatory methods that combine the vector of scores corresponding to each alternative into a single scalar for ranking purposes. This may be done by aggregating or averaging the individual scores of an alternative a_i against the set of attributes into a value r_i, which represents the overall contribution of a_i. Thus, r_i may be ordered in a set $\mathscr{R} = \langle r_1, r_2, \ldots, r_n \rangle$ such that $r_i \geq r_{i+1}$ or $r_i \leq r_{i+1} \forall\ i \in [1,n]$ holds. The simplest method in this category and probably one of the most used is the *Weighted Sum Model* (WSM) (Zanakis et al., 1998), that consists of computing r_i as the aggregation of the weighted criteria of the alternative a_i, as follows:

$$r_i = \sum_{j=1}^{m} w_j d_{ij} \tag{1}$$

where w_j is the weight assigned to attribute j and d_{ij} is the score of a_i in terms of b_j. *Weighted Product Method* (WPM) (Zanakis et al., 1998) is similar to WSM by replacing the sum by product, and where the weight is used as a power of each score:

$$r_i = \prod_{j=1}^{m} d_{ij}^{w_j} \tag{2}$$

WSM and WPM are simple methods to compute the overall scores of alternatives, but they fail in providing support for calculating weights, which are based on subjectivity of opinions that could be far from reality. A subgroup within this category corresponds to methods that order r_i values with regard to its distance to an ideal solution. *Technique for Order of Preference by Similarity to Ideal Solution* (TOPSIS) (Hwang and Yoon, 1981) aims at finding those alternative with the shortest distance from the ideal solution and the farthest from the negative-ideal solution. To this end, the Normalized Performance Matrix N is constructed as:

$$n_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{n} d_{ij}^2}} \tag{3}$$

TOPSIS computes next the weighted normalized values $d_{ij} = w_j n_{ij}$ and, based on them, the ideal solution A^* and the negative-ideal solution A^- as:

$$\begin{aligned} A^* &= \{\langle \max d_{ij} i = 1, 2, ..., n, j \in J_- \rangle, \langle \min d_{ij} i = 1, 2, ..., n, j \in J_+ \rangle\} \\ &\equiv \{d_{1*}, d_{2*}, ..., d_{n*}\} \end{aligned} \tag{4}$$

$$\begin{aligned} A^- &= \{\langle \min d_{ij} i = 1, 2, ..., n, j \in J_- \rangle, \langle \max d_{ij} i = 1, 2, ..., n, j \in J_+ \rangle\} \\ &\equiv \{d_{1-}, d_{2-}, ..., d_{n-}\} \end{aligned} \tag{5}$$

where $J_+ = \{j = 1,2,...,m\}$ s.t. j is a benefit attribute and $J_- = \{j = 1,2,...,m\}$ s.t. j is a cost attribute. The Euclidean distance between the alternative a_i with regard to the best condition A^+ and the worst condition A^-, denoted as d_{i+} and d_{i-}, respectively, are computed as:

$$d_{i*} = \sqrt{\sum_{j=1}^{m} (d_{ij} - d_{j*})^2}, \; i \in [1, n] \tag{6}$$

$$d_{i-} = \sqrt{\sum_{j=1}^{m} (d_{ij} - d_{j-})^2}, \; i \in [1, n] \tag{7}$$

Finally, the method ranks the alternatives in function of their similarity s_{i*} with regard to the ideal condition:

$$s_{i*} = \frac{d_{i*}}{d_{i*} + d_{i-}} \tag{8}$$

Therefore, $s_{i^*} = 1$ iff s_{i^*} holds the best condition and $s_{i^*} = 0$ iff s_{i^*} holds the worst condition.

Analytical Hierarchy Process (AHP) (Saaty, 1980) derives the weights and the scores based on pairwise comparisons of alternatives for each attribute in a hierarchy, typically a tree. Thus, for each pair of attributes (b_i,b_j) the relative importance of b_i against b_j is quantified in a scale of 1 (equally important) to 9 (overwhelmingly important) and, correspondingly, the relative importance of b_j against b_i is directly obtained as the inverse of this value. After computing these comparison values, the weights w_j may be then computed as the elements in the eigenvector associated with the maximum eigenvalue of the matrix. Similarly, AHP also uses pairwise comparison to determine relative importance of the scores for each alternative on each criterion. Then, AHP computes the AHP score of a_i as the aggregation of the products between each weight w_j and the value d_{ij}, in a similar way to WSM. The same author proposed years later *Analytic Network Process* (ANP) (Saaty, 1996), which structures the decision problem into a network instead of a hierarchy.

Outranking methods are based on the idea of preference of some criteria against others. An alternative outranks the other if it outperforms the other on enough criteria of enough preference and is not outperformed by the other option on any other criteria (Roy, 1991). Two representative methods in this category are ELECTRE (Roy, 1991) and PROMETHEE (Brans et al., 1984). ELECTRE is based on two concepts: concordance and discordance indexes. The concordance index $c(a_i,a_k)$ between a pair of alternatives (a_i,a_k) is:

$$c(a_i, a_k) = \sum_{j: d_{ij} \geq d_{kj}} w_j, \; j \in [1, m] \tag{9}$$

Note that $c(a_i,a_k) = 1$ if $d_{ij} \geq d_{kj}$ and $c(a_i,a_k) = 0$ if $d_{ij} < d_{kj}$ for all $j \in [1,m]$. In turn, the discordance index $d(a_i,a_k)$ between (a_i,a_k) is:

$$d(a_i, a_k) = \begin{cases} 0, & \text{if} \quad \forall\, j\text{: } d_{ij} \geq d_{kj} \\ \max\{d_{kj} - d_{ij}\}, & \text{if} \quad \exists\, js.\ t.\ d_{kj} \geq d_{ij} \end{cases} \tag{10}$$

The method establishes $\tilde{c}$ and $\tilde{d}$ as concordance and discordance thresholds, which correspond to the minimum and maximum thresholds, respectively, that are used to determine the relation of outranking. Thus, a_i outranks a_k iff two conditions hold: $c(a_i, a_k) \geq \tilde{c}$ and $d(a_i, a_k) \leq \tilde{d}$.

2.2. Smart city rankings

City rankings are based on the election of a set of n alternatives (i.e. cities) and a set of m attributes (i.e. indicators) through which alternatives are evaluated. An indicator is defined as a statistic or parameter that provides information on trends in the condition of some phenomenon (Hoornweg et al., 2007) relevant to the city, and it is represented as a number that can be comparable/standardized longitudinally (over time) and transversally (across alternatives). Subsequently, by ordering the overall scoring of each city, a ranking of cities can be obtained. We analyze in the following paragraphs four rankings used for smart cities classification: Cities In Motion Index (CIMI) (Anon., 2015), European Smart Cities Ranking (ESCR) (Giffinger et al., 2007), Green City Index (GCI) (Anon., 2012), and IDC Smart Cities Index (Anon., 2012).

The University of Navarra (Spain) computes annually the CIMI, a synthetic index that in 2015 classified 148 cities (55 capitals) from 57 countries worldwide along 10 dimensions. For each dimension, the authors define the set of indicators up to achieve a total of 72 and, for each indicator, its measurement unit and source (e.g. World Bank, UNESCO, QS Top Universities). Statistical clustering techniques are used in case of a missing indicator value. CIMI determines the weights and computes r_i by using the DP2 method, also called Pena's method or P2 Distance (Somarriba and Pena, 2009). DP2 computes the difference between the given value of an indicator d_{ij} and other value that is taken as reference. According to their r_i, CIMI classifies the cities into four groups: A) High Performance ($r_i \geq 90$); RA) Relatively High ($60 \geq r_i < 90$); M) Medium ($45 \geq r_i < 60$); and B) Low ($r_i < 45$).

ESCR was firstly published in 2007 and then annually since 2013. In 2015, ESCR selected 90 European cities from 21 countries from 300,000 to 1 million inhabitants to be classified along 6 dimensions. The ranking uses a total of 90 indicators, from which 15 belong to Economy, 10 to Governance, 31 to Smart Living, 11 to Smart People, 10 to Environment and 13 to Mobility. The method enables several values from different sources for each indicator, that are first standardized by applying z-transformations and then, they are aggregated to obtain the indices. A z-transformation results in a distribution with an average of 0 and a standard deviation σ of 1, and it is computed for each d_{ij} as $z_{ij} = \frac{d_{ij} - \overline{d_{ij}}}{\sigma}$, where $\overline{d_{ij}}$ is the average of the values of a_i across the attribute j. In case of unavailable values, the authors compute averages taking into account just the number of available values.

Siemens, as a worldwide leader provider in the industrial, healthcare, and energy sectors has created the Green City Index (GCI), aimed at measuring the environmental performance of more than 120 cities from 41 countries, that are compared at the continent level, due to the complexity of obtaining a universal set of indicators. Thus, the European GCI (EGCI) takes in consideration 30 European capitals that are evaluated across 8 dimensions along 30 indicators. The method of computation has not been published.

The Spanish company International Data Corporation (IDC) published in 2011 and 2012 the rankings of the Spanish smartest cities. This study considers the 44 largest Spanish cities (with more than 150,000 inhabitants). The novelty of this ranking lies on evaluating the cities across two groups of dimensions: a first group of 6 smart dimensions and a second group of 3 enabling technologies, as driving forces to promote smartness. For both the dimensions and enabling forces a total of 23 criteria and 94 indicators were selected. The results of IDC classify the cities into 4 groups: top 5 cities ordered by score; 5 contenders (i.e. cities that did a significant effort); players (i.e. cities that are moving in the right direction) and followers (i.e. cities behind their peers). Table 1 shows a summary of these rankings and their top-10 cities.

Beyond rankings, other frameworks for measuring the smart cities performance have been proposed. The methodology proposed in Lombardi et al. (2012) is based on ANP for establishing the interrelationship between 5 smart city dimensions (Governance, Human Capital, Environment, Living and Economy) with respect to a modified triple-helix model version, composed of university, industry, government, and that includes civil society as the fourth helix. The authors select a total of 60 urban indicators distributed along the six dimensions. The methodology calculates a supermatrix, which consists of weighted priority vectors of the elements that have been evaluated, and that serves as basis for determining the priorities of the city and as subsequent decision making processes. The work described in Lazaroiu and Roscia (2012) presents a fuzzy logic-based model for assessing the smart city under the energy efficiency perspective. This study considers 4 criteria (Smart Economy, Smart Environment, Smart Energy and Mobility and Smart Governance) and selects 18 smart city indicators related to energy and sustainability. The methodology works as follows: judges express their opinion on the criteria through fuzzy numbers and evaluate the indicators with respect to all evaluated criteria, resulting into a matrix of $n \times m$ items, where n is the number of judges and m is the number of indicators. The average values of the indicators and their weights are then calculated. The final weights are obtained by means of a process of *defuzzification*, which normalizes the average weights obtained. The framework proposed in Carli et al. (2013) classifies the performance indicators of a smart city under two points of view: level of objectivity (i.e. objective and subjective) and the methodologies and technologies used for their calculation (i.e. traditional tools, innovative tools based on data sensing and mining of physical and social infrastructure). This framework was used to classify the ESCR indicators: the results reported that it presents an overall significant content of subjective indicators and there is a margin to use new sources of data acquisition. In Albino et al. (2015) a wide spectrum of definitions, concepts, dimensions and indicators of smart cities is analyzed. The study suggests that the assessment of the smartness of a city should be tailored to the particular vision of each city.

Table 1
City rankings summary.

CIMI	ESCR	EGCI	IDC
Cities: 148	Cities: 90	Cities: 30	Cities: 44
Countries: 57	Countries: 21	Countries: 30	Countries: 1
Indicators: 72	Indicators: 90	Indicators: 30	Indicators: 94
Dimensions: 10	Dimensions: 6	Dimensions: 8	Dimensions: 9
Governance	Economy	Air quality	Government
Urban planning	Governance	Environmental governance	Buildings
Public management	Smart living	$C0_2$	Mobility
Technology	Smart people	Energy	Energy & environment
Environment	Environment	Buildings	Services
International exposure	Mobility	Transport	People
Social cohesion		Waste & land use	Economy
Mobility & transport		Water management	ICT
Human capital			
Economy			
Top-10 cities			
London	Stockholm	Copenhagen	Barcelona
New York	Kobenhavn	Stockholm	Santander
Seoul	Goteborg	Oslo	Madrid
Paris	Amsterdam	Vienna	Málaga
Amsterdam	Helsinki	Amsterdam	Bilbao
Vienna	Aarhus	Zurich	Valladolid
Tokyo	Malmo	Helsinki	Zaragoza
Geneva	Frankfurt	Berlin	Vitoria
Singapore	'S-Gravenhage	Brussels	San Sebastián
Munich	Stuttgart	Paris	Pamplona

A new paradigm of smart cities, called Human Smart Cities, argues that the human dimension is what really becomes smart a city (Oliveira and Campolargo, 2015; Oliveira et al., 2014; de Oliveira, 2016). The human smart city concept is built on top of the smart city concept, where the citizens play a very active, participatory role in the co-design of solutions in cooperation with the governments. A human smart city is therefore a citizen-driven approach on a smart, all-inclusive and sustainable environment (Oliveira and Campolargo, 2015). Two examples of initiatives supporting this vision are the MyNeighbourhood project (M. Project, 2013-2015), implemented in Lisbon, Milan, Aalborg and Birmingham, and the Human Smart Cities Network (Anon., 2015) that includes 27 cities in 16 countries.

2.2.1. City rankings suitability for smart cities

The rankings analyzed introduce the *dimension* concept, additionally to alternatives (cities) and attributes (indicators). A dimension of a smart city refers to *a field of realization of a smart city* (Albino et al., 2015) and each dimension is characterized by a set of attributes or indicators. Thus, rankings are a valuable instrument to measure the degree of urban development of the cities with regard to a set of indicators related to various dimensions. In contrast, rankings may present some limitations. Firstly, the availability of the values of indicators, which can not always be obtained directly from the source, but instead they have to be inferred through statistical techniques. Secondly, while the discussion is mainly focused on the position occupied by the samples considered in the study, the selection of indicators and the method of calculation used are frequently neglected (Giffinger and Gudrun, 2010). Thirdly, the selection of the indicators is of utmost importance since they impact on the ranking precision. More specifically, the rankings and tools previously described, generally overlook or do not draw enough attention to the need of incorporating ICT as part of the evaluation criteria of the smart city materialization. For instance, in the case of CIMI, technology is a *vertical dimension* expressed as 8 indicators: FIS (Fixed broadband Internet Subscribers per 100 hab.), BIU (Broadband Internet Users), NIAR (No. of Internet Addresses Registered), NBW (No. of Business grade WIFI hotspots), NF (No. of Facebook users per 1000 hab.), NMPC (Mobile Numbers per capita), QMW (Quality of Municipality Websites), and ICI (Innovation Cities Index). This means that only 11% of indicators employed by CIMI are based on some technological aspect, mainly related to the digitalization degree of the city (e.g. number of Internet users, number of mobile numbers per capita, number of WiFi hotspots) without taking into account what is being done in the city to realize the smart city concept.

Table 2
Number of digital indicators vs. total number employed in Giffinger and Gudrun (2010) and Cohen (2012).

	ESCR (Giffinger and Gudrun, 2010)		Cohen (Cohen, 2012)	
Dimension	Digital	Total	Digital	Total
Smart economy	2	12	2	3
Smart mobility	2	9	3	3
Smart people	1	15	3	3
Smart environment	1	9	3	3
Smart governance	2	9	2	3
Smart living	0	20	1	3

Even though ESCR is originally intended to classify smart cities, it just includes a few specific technology-based smart city indicators, as stated in Jucevicius et al. (2014), which faces the problems of identifying the most suitable factors for evaluation of smartness of the city and the relationship between "smartness" and digital dimension are. To do that, the authors compare the smart city factors used in ESCR (Giffinger and Gudrun, 2010) and Cohen (2012) by measuring the number of digital indicators that are used with regard to the total number of indicators. The results are shown in Table 2, where the number of digital indicators can be compared against the total number of them.

Similarly to ESCR, EGCI also lacks technological indicators. The IDC index, in turn, considers ICT as an enabling force (not as dimension) and measures specifically its maturity level in terms of data availability, resulting into three levels: open data, valuable information, and ubiquitous information.

Other studies have argued the lack of a technological dimension when evaluating smart cities. In Shi et al. (2018), AHP, AHP-BP (Back Propagation), and AHP-ELM (Extreme Learning Machine) models are compared to evaluate the intelligent development level of 151 cities in China through 16 urban indicators, which were not published. To the view of their results, the authors suggest the need to enrich their evaluation system by including technological innovation capability, among others. Cavada et al. (2014) review the plethora of contradicting smart city definitions found in the literature and show the lack of a robust, coherent definition. Their authors review the smart city concept along 3 themes: 1) Information Communication Technology; 2) Resilience and Sustainability; and 3) Innovation and Business. The definitions are then matched against 3 stakeholders: People, governance and companies. As a result, the authors present the Smart Cities Matrix, from which they conclude that Smart Cities Governance yet appears to ignore the role of ICT while People and Companies pay a still moderate attention with regard to the themes 2) and 3). The IBM's report (Susanne Dirks and Dencik, 2009) proposes a model that includes only very general factors (e.g. city services, water, communications, transport, business), which make it harder to notice the technological dimension.

Since it is commonly accepted that technology constitutes the cornerstone for the smart cities materialization, a ranking for smart cities should necessarily include criteria related to ICT and smart cities evaluation to help in quantifying the effort done by the cities to achieve smartness along the dimensions involved. In the absence of such ICT dimension, a city ranking is not necessarily adequate for a smart city, as it does not collect specific criteria neither indicators for smart cities classification. Thus, our vision of smart city ranking differs slightly to that of the main objective of a city ranking: while a city ranking is a metric of the urban development, a smart city ranking evaluates the materialization degree of the smart city concept. To this end, a smart city ranking should incorporate specific indicators to measure not only the *quantity* of technological infrastructure, but also the *quality* and the smartness degree of the provided services.

3. An MADM methodology for ranking smart cities

This section aims at describing the proposed methodology, framed within Multi-Attribute Decision Making (MADM) context, to design a specific ranking for smart cities classification. In contrast to the rankings examined in Section 2.2, we explicitly introduce the concept of *ICT dimension* in the proposed methodology to represent a set of ICT-based attributes for evaluating the other vertical dimensions, thus providing a transversal ICT dimension. The aim of this ICT dimension is to incorporate smartness and technological information as a part of the quantification method in order to calculate the materialization level of the smart city concept carried out by the city. Next, we describe our methodological approach for ranking smart cities.

3.1. Method

Let us start with the definition of a set of n smart cities (alternatives) $A = \{a_1, a_2, \ldots, a_n\}$ to be evaluated against a set of m dimensions of interest, denoted by the set $B = \{b_1, b_2, \ldots, b_m\}$. Examples of these dimensions are smart mobility, smart parking, and smart energy. In addition to these dimensions, let us define a *smartness* dimension Ω as a set of p indicators specifically related to both smartness services and ICT resources employed within a city. Each indicator $k \leq p \in \Omega$ is provided with a weight w_k. For each city and dimension, an indicator k takes one and only one observed value o_{ij}^k, which represents the contribution to the indicator k done by the city i in dimension j. Then, the decision matrix $\mathscr{D} = A \times B \times \Omega$ is computed as follows:

$$d_{ij}^k = n_{ij}^k w_k \tag{11}$$

where d_{ij}^k represents the weighted contribution to the smartness indicator k in the dimension j and at the city i, with $i \in [1,n]$, $j \in [1,m]$, and $k \in [1,p]$, n_{ij}^k is the corresponding normalized value of the observation o_{ij}^k, and w_k represents the importance of this attribute with regard to the set of attributes, i.e. $\sum_{k=1}^{p} w_k = 1$. In order to make the values of the observations directly comparable among indicators, Eq. (11) requires normalized values. To this purpose, a technique to normalize the raw values o_{ij}^k into the interval [0,1] should be used, as for instance, the Min-Max method:

$$n_{ij}^k = \frac{o_{ij}^k - \min\limits_k}{\max\limits_k - \min\limits_k} \tag{12}$$

where min$k$ and max$k$ correspond to the minimum and maximum values, respectively, among the values taken by the indicator k for a specific dimension j across the cities considered, i.e. $\min_k = \min(o_{ij}^k)$ and $\max_k = \max(o_{ij}^k)\ \forall\ i \in [1, n]$.

Since each smartness indicator k enables scoring individually each dimension j, we state that Ω is a transversal dimension to B, because common resources, infrastructure, and services deployed for different smart initiatives may be shared by the different dimensions or initiatives launched within the city. Therefore, two types of aggregation proceed: 1) dimensions aggregation for the city i with regard to an only smartness indicator k, that we denote as $\Omega_i|_k = \sum_{j=1}^{m} d_{ij}^k$ and 2) indicators aggregation with regard to the dimension j of the city i, denoted as $\Omega_i^j = \sum_{k=1}^{p} d_{ij}^k$. Thus, $\Omega_i|_k$ quantifies the smartness degree focused on the indicator k across the dimensions of the city, while $\Omega_i|^j$ represents the smartness degree specifically of the dimension j of the city i.

Next, we rank the overall contribution of each city to the smartness dimension Ω. To do that, let us denote r_{Ω_i} to the overall contribution of the city i across the smartness dimension, computed as the aggregation of the observations done of each smartness indicator in every dimension j, i.e. $r_{\Omega_i} = \sum_{j=1}^{m} \Omega_i|^j$ or, equivalently, $r_{\Omega_i} = \sum_{k=1}^{p} \Omega_i|_k$ (note that in both cases the same value r_{Ω_i} is obtained). The values r_{Ω_i} may be scaled up within the interval [0,100] as $\frac{r_{\Omega_x} \times 100}{\max(r_{\Omega_i})}$, with $i \in [1,n]$ where r_{Ω_x} is the score of the city $x \leq i$. Finally, by ordering r_i values in descendant

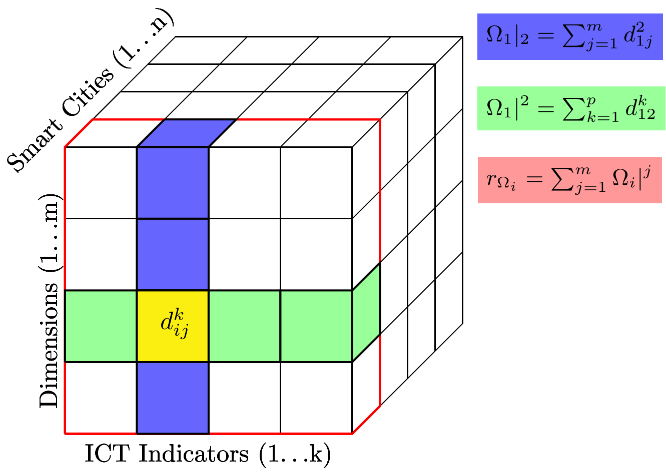

Fig. 2. A 3D structure representing the decision matrix for smart cities rankings.

order, we obtain the ranking $R = \langle r_{\Omega_1}, r_{\Omega_2}, ..., r_{\Omega_n} \rangle$, where $r_{\Omega_i} \geq r_{\Omega_{i+1}}, \forall i \in [1,n]$.

Consider Fig. 2 that represents graphically the relationships between cities (axis z), dimensions (axis y), and smartness indicators (axis x). Each value d_{ij}^k corresponds to the contribution of the city i, dimension j to the indicator k. The column in blue represents the items aggregated by dimensions for a specific indicator $k = 2$ and for the city $i = 1$, whose sum would be $\Omega_1|_2 = \sum_{j=1}^m d_{1j}^2$. The row in green represents the items aggregated by indicators for a specific dimension $j = 2$ and for the city $i = 1$, whose sum would be $\Omega_1|^2 = \sum_{k=1}^p d_{12}^k$. The final aggregation produces r_{Ω_i}, which is the sum of all items of the cube highlighted with a red line.

3.2. Indicators for ranking smart cities

The *smartness* dimension that we are proposing considers ICT indicators related to the main enabling technologies for smart cities realization: sensors and actuators, networking, platforms and services deployed, applications, standardization level, and metrics to determine their impact on the city. In order to select them for ranking smart cities, we need to explore these technologies. With this goal in mind, in the next subsection we describe the enabling technologies and, in the last subsection, we detail the indicators selected from them.

3.2.1. Enabling technologies

IoT and smart cities enabling technologies have been revised in many research works (Al-Fuqaha et al., 2015; Zanella et al., 2014; Atzori et al., 2010; Kim et al., 2014). We summarize them in the following paragraphs.

Objects/things are the part of the physical ecosystem of the smart city oriented to the data collection. To this end, a broad range of technologies may be employed (e.g. RFID Finkenzeller, 2003), wireless sensors (Akyildiz et al., 2002), FPGAs, SoC, CPSs or wearables devices) to enable classes of IoT devices, as identified by CASAGRAS project (Anon., 2008-2009) . An RFID tag is composed of a small microchip attached to an antenna and packaged as an adhesive sticker, sometimes used with sensors. Each RFID tag is identified by means of the Electronic Product Code (EPC), which is broadcasted to the surrounding area and is received by some RFID reader after launching a query. RFIDs are widely used in applications that require contactless identification such as smart cards, “autopiloting” cars, production automation and for building up the IoT ecosystem (Welbourne et al., 2009). Sensor nodes are equipped with several sensors (and/or actuators) for monitoring the near surroundings, a low-power microcontroller, a device for transmission and reception to/from other things (or humans) and some sort of power supply such as batteries or solar cells. Their behavior generally obeys to the pattern *sense-store-send-sleep*, continuously repeated during their lifetime. The spectrum of WSNs applications is unending as the sensors are more and more specialized and precise. IoT devices may be pervasive to the smart city infrastructure (e.g. in traffic lights, trash bins, buses), or make themselves explicit by means of ad-hoc devices and commercial devices such as Tmote, IRIS and Eko (MEMSIC), WiSense (WiSense Technologies), Arduino (Arduino), Waspmote (Libelium), NI WSN-3202 (National Instruments), and Shimmer (Intel). They also could be wearable devices or smartphones carried by citizens. Additionally, the IoT devices integrate a processing unit (e.g. microcontroller, microprocessor) that is provided with some application or service written by using the programming elements offered by the platform itself, and that fall into different abstraction levels (from bottom to up): the hardware interface, the programming language, and the operating system. In the first category, devices such as FPGAs or SoCs drop. Arduino falls into the second category as it lacks an operating system but instead it provides a C/C++-based reference language (Reas et al., 2007) for building applications. The third category refers to operating systems specifically developed to manage efficiently the limited resources of the devices and to supply high-level abstractions that simplify the programming of multi-purpose applications, as for instance TinyOS (Hill, 2003) , Contiki (Dunkels et al., 2004) and Mantis (Bhatti et al., 2005). IoT devices may also be less restricted devices such as Android and Raspberry Pi, which can integrate different sensors and support operating systems based on lightweight versions of GNU/Linux. The WISEBED (Anon., 2008-2011) project is aimed at the integration and interoperability of devices; its demonstrator employed 750 sensor nodes (200 iSense, 143 TelosB, 108 G-Node, 100, MSB-A2, 44 SunSPOT, 60 pacemate, 24 Tnode) distributed among 9 different sites.

Communication technologies. To realize the IoT vision, i.e. hyperconnected *things* at any time and any place, wireless communication technologies arise to meet both in- and intra-network requirements. Generally, IoT devices fit well into WPANs (Wireless Personal Area Networks) category, which are characterized for a low-rate traffic, low-power consumption, and low-range in the presence of lossy and noisy communication links, that is the dominating scenario. For this purpose, multiple standards have been proposed, such as IEEE 802.15.4, Bluetooth, and RFID. The former specifies the PHYsical layer (PHY) and the Medium Access Control layer (MAC) for Low-Rate WPAN (LR-WPAN). Bluetooth is mainly intended for communication of devices located at short distances, usually lower than 10 m, thus becoming very appealing for mobile devices and for wearable devices in the Body Area Networks field. Currently, there exist 4 specifications of Bluetooth, each one reduces the communication range and the energy consumption, and increases the data rate of the previous class, where class 4 is also known as Bluetooth Low Energy (BLE). As proximity technologies RFID and NFC (Anon., 2010) enable communication between two devices located at still shorter distances, approximately 10 cm or less. There exist 4 categories of RFID devices that use different frequency bands, where lower frequencies involve lower distances and lower costs. NFC (Near Field Communication) employs electromagnetic induction between a loop antenna to transmit/receive data within the ISM band of 13.56 Mhz at rates ranging from 106 to 424 Kbps, and where devices can be separated just a few centimeters. Differently from LR-WPAN technologies, UWB (Anon.) allows transmitting huge amounts of data (up to 480 Mbps) over a wide spectrum of frequency bands, with very low power and at short distances, thus providing High-Rate WPAN (HR-WPAN). These characteristics become UWB particularly useful for interchanging multimedia data in indoor environments, as for instance for implementing wireless monitors, transfer of data from digital camcorders, wireless printing and real-time location systems.

Beyond inter-things communication, the data interchange with any other type of device located at any other network is also required, for which Wireless Local Area Networks (WLANs) are employed, typically

Wi-Fi as it is the standardized product based on the IEEE 802.11 family. By extending the communication geographic range, cellular networks or Wireless Wide Area Networks (WWAN) as GPRS, LoRaWAN, SigFox and WiMAX are employed. LoRaWAN (Sornin et al., 2015) and SigFox (https://www.sigfox.com/) are intended to meet the specific requirements of IoT such as low power, unlimited number of devices, and low data rates over a long range of communication, where cellular networks fail due to energy efficiency issues and Wi-Fi is less adequate for long range applications. A LoRaWAN architecture uses a star-of-stars topology, where end nodes (e.g. *things*) are bidirectional and transmit a small amount of data in one single hop to one or several transparent gateways, which forward the received packets towards the cloud-based network server by using standard IP connections. The network server is aimed at filtering the packets, performing security checks, or managing adaptive data rates. A LoRaWAN gateway covers more than 10 km and it is comparatively cheaper. The entire city of Amsterdam, for instance, is covered with 10 gateways at a cost of 1200 dollars. LoRaWAN is being supported by LoRa Alliance, an open, non-profit association with members worldwide. Its main competitor, SigFox, provides global cellular connectivity by using Ultra-Narrow Band (UNB). SigFox technology enables connecting devices located at very long distances that transmit extremely small amounts of data (up to 12 bytes per message) and up to 140 messages per device and per day, which is however, enough for many IoT applications. The Sigfox network is currently deployed or being rolled out in 19 countries and registering over 7 million devices in its network and its presence in 60 countries is expected within the next 5 years.

The 802.11 and 802.15.1,3,4 IEEE standards regulate the PHY and MAC layers within the communication protocols stack. On top of MAC, networking and routing protocols are still needed in order to provide end-to-end communication of *things*. ZigBee Specification (2005) has standardized the network and application layers on top of IEEE 802.15.4. Internet network protocols, IPv4 and its successor IPv6, will continue providing connectivity and addressing in IoT, even to the objects with more limited processing capabilities. With this idea 6LoWPAN (Thubert and Hui, 2015) (IPv6 over LR-WPAN) defines the encapsulation and header compression mechanisms that allow IPv6 packets to be transmitted over IEEE 802.15.4 networks. Table 3 shows a comparison of wireless technologies.

Application-level services. On top of the communication protocols, the application requirements and functionalities are described through top-level protocols, which can be classified in three groups attending to the data access architecture: REST-based model (e.g. CoAP), Publish/Subscribe pattern (e.g. MQTT, AMQP, and DDS), and Instant messaging (e.g. XMPP). The REST model (Fielding and Taylor, 2002) defines the exchange of messages between clients and servers over HTTP/TCP to access the Internet resources. CoAP (Bormann et al., 2015) (Constraint Application Model) is similar to REST in the sense that in a CoAP interaction a client sends a request for a resource identified by an URI to a server which, in turn, returns the response to the client. Differently to REST, CoAP deals with these interchanges asynchronously over a datagram-oriented transport such as UDP, and considers the limited processing capabilities of clients and servers in an IoT scenario. REST and CoAP are currently used by many applications for smart cities. An example is Padova city (Italy), which has held a demonstrator of structural health, waste management, air quality, and noise monitoring, traffic congestion, city energy consumption, smart parking and lighting, and automation and salubrity of public buildings (Zanella et al., 2014). The demonstrator consisted of 300 sensor nodes deployed in the University of Padova to evaluate a proof-of-concept architecture based on REST web services, through which citizens and authorities access to data collected by peripheral nodes with capabilities of sensing CO, temperature, humidity, vibrations, noise, and benzene. The nodes use IEEE 802.15.4 and transmit data to gateways with IPv4/IPv6 access.

In the publish/subscribe pattern, subscribers (consumers) register their interests of data and publishers transmit relevant data (producers); the responsibility of the communication between publishers and subscribers can fall under a broker for message distribution, as for instance in the case of MQTT and AMQP. There exist two specifications of the former protocol: MQTT (Anon., 2016) works on top of TCP while MQTT-SN (Hunkeler et al., 2008) works on non-TCP /IP networks as ZigBee. In the AMPQ (Standard) specification, the publishers register first their messages in entities called exchanges, which distribute message copies to queues using a set of rules called bindings. In turn, consumers subscribe to queues to receive a copy of each message put on that queue. The AMQP broker then deliver messages to consumers subscribed to queues. The DDS standard (Pardo-Castellote, 2003) requires any implementation to be broker-less, which means that the DDS application can communicate without any mediation. This model fits very well into the development of constrained applications for IoT (Anon., 2014), and simplifies greatly the programming for distributed applications. XMPP (Saint-Andre, 2011) provides a technology for the asynchronous, end-to-end communication of peers that interchange persistent XML streams on a distributed network of globally addressable (based on DNS), presence-aware clients and servers. XMPP arises to overcome the problem of an increasing number of instant messaging clients that could not talk to each other, and some of its features as Efficient XML Interchange (EXI), Multicast DNS (mDNS) and DNS Service Discovery (DNS-SD) are being now actively used for IoT implementation.

Middleware architectures and platforms. To address the interoperability issue, several platforms have been proposed. The FIWARE

Table 3
Wireless communication technologies for *things*.

Name	Standard	Frequency	Bandwidth	Range	Application	Consumption
Bluetooth1	IEEE 802.15.1	2.4-2.485 Ghz	1 Mbps	100 m	WPAN	100 mW
Bluetooth2			3 Mbps	10		2.5 mW
Bluetooth3			24 Mbps	1		1 mW
BLE			24 Mbps	0.5		0.5 mW
ZigBee	IEEE 802.15.4	868,915 Mhz; 2.4 Ghz	250 Kbps	100 m	WSN, LR-WPAN	~24(TX) ~27(RX)mW
UWB	IEEE 802.15.3	3.1–10.6 Ghz	110–480 Mbps	10 m	HR-WPAN	~ 227 mW
RFID (LF)	ISO 14223, ISO/IEC 18000-2	125–134 Khz	Low	< 50 cm	Contactless identification	*Passive*
RFID (HF)	ISO 14443, ISO 15693	13.56 Mhz	High	~1 m		
RFID (UHF)	ISO 18000-6C	865–868 Mhz-Europe 902–928 Mhz-N. America	Medium	12 m		*Active*
RFID (μwave)	ISO 18000-4	2.45–5.8 Ghz		1–2 m		
NFC	ISO 13157	13.56Mhz	106–424 Kbps	4–20 cm	Contactless payment systems	< 15 mA
Wi-Fi	IEEE 802.11 a/b/g	2.4 Ghz; 5 Ghz	Up to 54 Mbps	100 m	WLAN	High (limited)
LoRaWAN	LoRaWAN R1.0	867–869 Mhz (Europe) 902–928 Mhz (N. America)	0.25–50 Kbps 0.98–21.9 Kbps	10 km	LPWAN, IoT	+14 dBm(TX) +30 dBm(TX)
SigFox	SigFox	868 Mhz-Europe 900 Mhz-N. America	300 bps	1000 km	LPWAN, IoT	25 mW (uplink) 500 mW (downlink)

(Anon., 2011-2014) project, sponsored by European Union, aims at providing the foundations for the Future Internet by enabling an innovative infrastructure for cost-effective creation and delivery of versatile digital services, providing high QoS and security guarantees. In the context of IoT, FIWARE deals with the interoperability issue, and it is concerned with the architecture, implementation of *generic enablers* associated to things in order to become available, searchable, accessible, and usable resources, and with the definition of IoT use-case scenarios that exploit such architecture. Several cities (e.g. Seville, Trent, Turin, Lisbon) have deployed FIWARE data centers and companies, public organisms, and citizens are sharing information and data in an homogeneous way. The SOFIA (Anon., 2009-2011) (Smart Objects for Intelligent Applications) project involved eighteen European partners into the search of making information from the physical world available for smart services. A key aspect of this project is the search of interoperability among many heterogeneous IoT devices and embedded systems; thus, SOFIA provides a platform to support the interaction among entities and to create innovative services adapted to the user's situation and profile. To this end, SOFIA provides tools for easily developing smart applications on top of the architecture. 7 cross-domain pilots were implemented in 4 European Countries, 5 of them related to smart cities. Plant IT Urban Operating System (Anon., 2016) (Plan IT UOS) is a cloud-based middleware platform developed by Living PlanIT aimed at achieving integration, open access, real-time optimized monitoring, scalability, data alignment, ease of application development, and low cost. The Plan IT UOS platform enables the development and deployment of urban technology and connected devices, and provides flexible and supervisory real-time control, data acquisition and life cycle management. The company chose 1700 ha of land near Porto (Portugal) to develop a "city-from-scratch", called PlanIT Valley, with about 100 million sensors to test the platform. City Protocol (Anon., 2015) is a collaborative framework aimed at defining a common view for cities of any size and type, through a common vocabulary, in order to create the Internet of Cities for the benefit of all citizens. Currently, a non-profit international association that comprised 35 countries, 70 organizations and more than 300 experts is sponsoring the description of the city anatomy, by means of the definition of city indicators, ontologies, data models, patterns, and open sensors platform. Additionally, corporations such as Siemens and Oracle are also developing their own smart city platforms. The Oracle's solution (Oracle, 2013) for city governments is an evolution of the e-administration to offer a multichannel homogeneous interaction with the citizen. Siemens City Intelligence Platform (CIP) (Lehofer et al., 2016) focuses on unification of the management of data collected in the city. Meanwhile Oracle's platform is already deployed in cities, CIP seems to be a research effort oriented to provide cities with self-learning capabilities. Table 4 shows a comparison of the main features of several smart cities platforms. The IoT-A (Bassi et al., 2013) project pursues the integration of frameworks/architectures for WSN, RFID and other emerging IoT related technologies, such as Model Driven Engineering, Aspect-oriented programming, views and perspectives.

Syntactic and semantic interoperability. In the search of interoperability, the uniform description of processes, components and data makes them be effectively and automatically understood, used and shared across sensors and other sensing systems. SensorML (Anon., 2014) is an OMG standard aimed at describing syntactic interoperability through the processes associated to the measurement, observation, and post-measurement transformation, through the processing and observation components such as the sensors and actuators (e.g. particular model, type, configuration), and through the processing and analysis of the data observed (e.g. geolocation, aggregation, alerts). The standard defines an XML schema grammar as well as a set of patterns that represent the XML implementation of conceptual models, in such a way that any process described in SensorML is discoverable and executable. SensorML 2.0 provides a method for IoT by enabling an encoding for describing sensors *(things that measure)*, actuators *(things that act)*, and processors *(things that calculate)*. To deal with the complexity and the size of the XML messages to be transmitted and processed (which could result prohibitive for many IoT devices in terms of memory and energy), EXI (Schneider and Kamiya, 2008) proposes an efficient way to reduce the size of XML documents in a compression rate of 20:1. To address semantic compatibility issues, ontologies and semantic web are two enabling technologies since they gain expressiveness in the representation of sensor descriptions and their observations, which will be useful for classification and reasoning. On the one hand, ontologies allow building a formal vocabulary of concepts and relationships, thus providing the syntax and semantics required. On the other hand, semantic web promotes the use of the Web as a medium for data and information integration, by means of common data formats and exchange protocols. These technologies are the basis of the so-called *web of things*, which promotes the reuse of available and widely popular web protocols to make data and services offered by things more accessible to humans and things.

Data analytics and storing. Big Data combines large-scale computation, data-intensive techniques, and mathematical models to implement data analytics (Kune et al., 2016) on a huge volume and variety of (non-)structured data proceeding from the mass of *things*. Several projects have merged smart cities and Big Data. For instance, Transport for London (Anon., 2016) integrated in its smart card Oyster a RFID chip to transmit the moment of time and the location of a carrier when passing the automatic barriers of the transport network. The analysis is focused on investigating the habits of travelers and on making predictions about their locations. The Bike Share Map project (O'Brien, 2016) collects real-time data of public services of bikesharing around the world. The project accounts the number of docking stations, docks, bikes in docks and in use to make statistics of occupation in 155 cities. Big Data is then employed to extract advanced conclusions about the cultural behavior of citizens in accordance with their origins and destinations. At these scales, the cloud computing paradigm providing any infrastructure, platform, and software as a service offers an appealing model for data accessing. The cloud enables to establish direct relationships among service providers (producers) and tenants (consumers) and a business model where providers may find economies of scale by sharing resources and where tenants may find service elasticity by paying only for the resources that use. Thus, *things* could act both as providers (by using cloud services for publishing data) and tenants (by using cloud services for recovering information) while Big Data can be used to extract knowledge upon huge volumes of data. There exist several cloud platforms suitable for IoT as GoogleCloud, Amazon, OpenIoT, Chatty Things and Xively. A good survey is reported in Al-Fuqaha et al. (2015).

Table 4
Smart cities platforms. **Legend:** ⚠ : Only visualization, no control. **A:** Smart City-specific; **B:** Device Integration; **C:** Common Vocabulary; **D:** Simulation; **E:** City Services; **F:** 3D visualization; **G:** 2D visualization.

Smart city platform	A	B	C	D	E	F	G
FIWARE	✗	✓	✓	✗	✗	✗	✗
SOFIA	✗	✓	✗	✗	✗	⚠	⚠
PlanIT UOS™	✓	✓	✓	✓	✓	✗	✗
City Protocol	✗	✓	✓	✗	✗	✗	✗
Siemens CIP	✓	✓	✓	✓	✗	✗	✓
Oracle	✓	✓	✓	✗	✗	✗	✗

3.2.2. Election of indicators

We have selected $p = 38$ ICT indicators for elaborating our proposal of smart city ranking. The list of indicators, its type (S: smart or ICT), name and description are shown in Table 5.

The process of selection of indicators is an exercise of utmost importance with impact on the ranking results. The indicators selected have been extracted from the set of enabling technologies previously reviewed, and two categories more: standardization level and

Table 5
Indicators of the *smartness* dimension. **Legend: ICT:** ICT indicator. **S:** Smartness Indicator.

k	Type	Description	Relevance to the smart city
NMA	S	No. of magnitudes	No. of distinct variables to be monitored (e.g. noise, pollution, trash level)
NSE*	ICT,S	No. of sensors/actuators	No. of sensors and actuators deployed on the city for collecting individual magnitudes
NCS	ICT	no. of classes of devices	No. of different technologies employed by the devices
NON	ICT	No. of devices	No. of devices integrating sensors and actuators that have been deployed on the city
NBR	ICT	No. of bridges/gateways	Number of gateways . This is an indicator of the effort done on the interoperability issue.
CAS	S	Coverage area of devices	The surface of the city that is covered by devices.
FLS	ICT	Reprogramming support	The capability of (semi-)automatic reprogramming of the ioT device's behavior. This is an indicator of its autonomy level.
SIZ	ICT	Data size	Average size of data (in TB) collected per unit of time (e.g. day, week, month)
NOO	S	No. of observations	No. of observations per unit of time that suggests the volume of information to be managed
NCT	ICT	No. of network technologies	No. of communication technologies employed. This represents the connectivity level achieved in the city and the municipalities awareness to enable citizens keep connected.
NWI	ICT	No. of WIFI hotspots	Number of Wi-Fi access points in the city per 1000 inhabitants
PDI	ICT	Device interoperability	% of devices that are able to communicate with others
PSI	ICT,S	Semantic compatibility	% of devices that include some strategy for implementing semantic compatibility
ALM	S	Alarms management	Does the city support at least one initiative that implements real-time notification of the interest events? (Yes/No)
RTM	S	Real-time support	Are data processed in real time to enable time decision making process? (Yes/No)
DAT	ICT	Data analytics	Does the city support at least one initiative that implements data analytics on the data collected (e.g. Big Data, data mining)? (Yes/No)
NOP	ICT	No. of computation units	No. of nodes that constitute the core of the smart city platform
SEC	ICT,S	Security issues	Does the city implement cipher, authentication, authorization, data protection and other issues related to security ?
WIU	ICT,S	Writing interface for users	Does the city provide interfaces to citizens, so they may write/upload their own data to a smart city platform? (Yes/No)
WIT	ICT,S	Writing interface for things	Does the city provide interfaces to devices, so they may write/upload the data collected to a smart city platform? (Yes/No)
RIU	ICT,S	Reading interface for users	Does the city provide interfaces to citizens, so they may read/download the data stored from the smart city platform? (Yes/No)
RIT	ICT,S	Reading interface for things	Does the city provide interfaces to devices, so they may read/download the data stored from the smart city platform? (e.g. Yes/No)
API	ICT,S	SDK availability	Does the city provide interfaces to citizens, so they can write their own smart city applications? (e.g. Yes/No)
NSA	S	No. of smart applications	No. of apps freely available to citizens, providing smart services, and implemented both by municipalities, citizens, and third-parties
APU	ICT	% of use	Average percentage of use of smart applications
NSD	S	No. of dimensions	Number of smart dimensions of interest for the city
APP	ICT	No. of apps developed	No. of apps developed related to the smart cities.
SDA	S	No. of data sets	No. of data sets that are available for citizens
DAC	S	Data access API	Does the city provide an interface for reading/visualization of the sets of data?
NDO	S	No. of downloads	Average percentage of apps downloaded w.r.t. the total population
ODC	S	Open data to citizens	Does the city make available the data to everyone to use and republish as they wish and without restrictions?
WEB	S	No. of page views	No. of visits received by the website (e.g. search of apps, web pages)
NSN	S	No. of social networks	No. of social networks mostly used at local/national level
NSU	S	% social network users	Avg. percentage of social network users (e.g. at local/national level). This suggests the level of digitalization of the city.
NST	ICT,S	No. of smart city standards	No. of standards related to smart cities considered by the city (e.g. local/national level)
KPI	S	No. of metrics	No. of metrics oriented to determine the progress achieved by the smart initiatives
MET	S	No. of available metrics	No. of metrics within the set of KPI with available data to compute the improvement
AVK	S	Average improvement	The average percentage of improvement achieved by MET

Table 6
Classification of the indicators into enabling technologies categories.

Category	Indicators	References
Objects/things	NMA, NSE, NCS, NON, NBR, CAS	Anon. (2008-2009,-), Akyildiz et al. (2002), Bhatti et al. (2005), Dunkels et al. (2004), Finkenzeller (2003), Hill (2003), Welbourne et al. (2009)
Networking	FLS, NCT, NWI	Anon., ZigBee Specification (2005), Anon. (2010), Finkenzeller (2003), Sornin et al. (2015), Thubert and Hui (2015)
Syntactic & semantic interoperability	PDI, PSI	Anon. (2009-2011, 2014), Compton et al. (2012), Fielding and Taylor (2002), Pardo-Castellote (2003), Saint-Andre (2011), Schneider and Kamiya (2008), Standard
Application-level services	ALM, RTM, WIU, WIT, RIU, RIT, API, APU, NSD, APP, DAC, NSA, NDO, WEB, NSN, NSU	Anon. (2016), Bormann et al. (2015), Giffinger et al. (2007), Hunkeler et al. (2008), Paganelli et al. (2014), Zanella et al. (2014)
Middleware architecture & platforms	NOP, SEC	2011-2014), Barcelona City Council (2012), Anon. (2015, 2016), Bassi et al. (2013), Oracle (2013)
Data analytics & storing	SIZ, NOO, DAT, SDA, ODC	Anon. (2016), Al-Fuqaha et al. (2015), Kune et al. (2016), O'Brien (2016)
Standardization	NST	Anon. (2008-2009, 2014), Pardo-Castellote (2003), Standard
Metrics	KPI, AVK, MET	Anon. (2012,?, 2015), Giffinger et al. (2007)

evaluation metrics. They are intended to show the quantity of resources employed and if a certain feature of smart city is being used or not. The reason to focus on technologies, standardization level, and evaluation metrics is the one, already mentioned, about the general agreement on the usage of ICT for smart cities realization. Specifically, we have considered two aspects: its scientific and technical relevance, which represents the interest of the research community on the topic; and its practical relevance, which shows its usage in testbeds, pilots, and demonstrators. In Table 6 we have classified the indicators into the categories described; the last column provides a selection of references to publications and projects where an indicator has been investigated or employed.

Each indicator will be provided with a single value o_{ij}^k, which is then normalized (n_{ij}^k) and weighted with w_k to obtain d_{ij}^k. Most of the indicators are numeric, e.g. NMA, NSE, NCS, because they are mainly related to the quantity and coverage of technological infrastructure deployed on the city. Other indicators may be simply expressed as " Yes/No", e.g. SEC, WIU, API, because they are more related to the quality or to the implementation of services itself in the city. Thus, the counter of values " Yes" may be interpreted as a greater engagement

Table 7
$\Omega_{i|k}$ and n_i for Santander, Seoul, New York **NA:** Not available. **Y:** Yes. **N:** No. $\Omega_{i|k}$ for NSE, NON, NOO, NOP, NWI, NDO, WEB in miles. NSU at national level.

	$\Omega_{i\|k}$			n_i		
	Santander[1]	Seoul[2]	NY[3]	Santander	Seoul	NY
NMA	26	19	38	0.364	0	1
NSE	24.8	NA	NA	0	0	0
NCS	7	15	15	0	1	1
NON	14.2	31.1	835.5	0	0.020	1
CAS	34.76	192	789	0	0.208	1
NCT	10	12	6	0.66	1	0
NBR	31	NA	NA	0	0	0
NOO	305.0	NA	NA	0	0	0
FLS	Y	N	N	1	0	0
SIZ	450	NA	NA	0	0	0
NWI	0.84	0.99	0.17	0.813	1	0
PDI	Y	N	N	1	0	0
PSI	Y	N	N	1	0	0
ALM	Y	Y	Y	1	1	1
ODC	Y	Y	Y	1	1	1
DAT	Y	Y	Y	1	1	1
RTM	Y	Y	Y	1	1	1
NOP	NA	1400	NA	0	0	0
NSN	4	44	2	0.047	1	0
NSU	48.83	52.07	59.63	0	0.299	1
SEC	Y	Y	Y	1	1	1
WIU	Y	Y	Y	1	1	1
WIT	Y	Y	Y	1	1	1
RIU	Y	Y	Y	1	1	1
RIT	Y	N	N	1	0	0
API	Y	N	Y	1	0	1
NSA	8	6	10	0.5	0	1
APU	11.1	75	0.2	0.146	1	0
NSD	5	4	7	0.333	0	1
APP	15	37	55	0	0.55	1
SDA	87	580	1587	0	0.528	1
DAC	Y	Y	Y	1	1	1
NDO	19.7	3.000	13	0.002	1	0
WEB	1.2	7737.5	503.3	0	1	0.064
NST	15	4	3	1	0.083	0
KPI	18	9	15	1	0	0.571
AVK	75.5	65	68.5	1	0.859	0
MET	1	3	9	0	0.25	1
			$\sum$ (out of 38)	19.87	18.81	21.63
			r_{Ω_i} (out of 100)	**52.31**	**49.52**	**56.93**

[1] Santander Data Sources: 1) SmartSantander (2013): http://www.smartsantander.eu/; 2) Red Ciudades Inteligentes: http://www.redciudadesinteligentes.es/; 3) Open data: http://datos.santander.es/data.

[2] Seoul Data Sources: 1) Smart Cities Seoul: a case study (2013):https://www.itu.int/dms_pub/itu-t/oth/23/01/T23010000190001PDFE.pdf; 2) Seoul e-Government: http://citynet-ap.org/wp-content/uploads/2014/06/Seoul-e-Government-English.pdf; 3) Seoul Mobile website: https://m.seoul.go.kr/; 4) Ubiquitous City in Korea. Services & Enabling Technologies (2011): https://www.tekes.fi/globalassets/global/ohjelmat-ja-palvelut/ohjelmat/ubicom/aineistot/raportit/korea/ubiquitouscityinkorea.pdf.

[3] New York Data Sources: 1) Building a Smart + Equitable City (2015): http://www1.nyc.gov/assets/forward/documents/NYC-Smart-Equitable-City-Final.pdf; 2) NYC Open Data: https://nycopendata.socrata.com/; 3) Drinking Water Supply and Quality Report (2014): http://www.nyc.gov/html/dep/pdf/wsstate14.pdf.

and awareness of the municipalities to realize the smart city concept. We have also included other indicators related to the standardization level (e.g. NST) and to the fulfillment level of objectives (e.g. KPI, AVK, MET).

4. Case study: Santander, Seoul, and New York

We present a case study that considers three cities to be ranked according to the ICT dimension proposed: Santander, Seoul, and New York, with a number of inhabitants of 177,383, 10,442,426 and 8,406,000, respectively. These cities were selected because they present a high availability of the values of the indicators proposed. The process starts with the collection of the values for each indicator and for each city. This step faces the challenge of finding such raw data, because frequently they are not available, require some kind of computation or statistics from other indicators, or could be expressed in different units. After compilation, values are normalized as explained in Section 3. Table 7 presents the aggregated values for each indicator k and each city i, i.e. $\Omega_{i|k}$ in the first three columns, and in the next three columns their corresponding normalized values according to the Min-Max method (n_i). For the sake of simplicity, we have considered that all the indicators have the same weight. For normalization purposes, NWI (number of WIFI hotspots) was standardized by population resulting into the ratio between number of WIFI access points and 1000 inhabitants; and `Yes` takes the value 1 and `No` the value 0. The indicators whose values are not available for at least one of the cities are not taken into account for the computation of the subindex r_{Ω_i}. The last row reports the score of the smartness dimension of each city ir_{Ω_i} in the interval [0,100].

In the three following subsections we summarize the information provided by municipalities with regard to the indicators to elaborate Table 7.

4.1. Santander smart city

The city of Santander, located in the North of Spain, has held the largest pilot ever developed in a research project on smart cities, becoming the city one of the smartest cities around the world. The SmartSantander project has implemented initiatives in 5 smart domains: traffic, lighting & environment, parks, mobile environment monitoring, and buildings & energy, which have yielded 8 smart applications: environmental monitoring, outdoor parking management, traffic monitoring, mobile environment monitoring, precision irrigation, guidance to parking lots, participatory sensing, and augmented reality. 31 gateways, 1516 fixed nodes, 175 mobile nodes and 2500 tags provide a total of 3029 fixed sensors, 1750 mobile sensors and more than 20,000 sensors proceeding from participatory smartphones. Such deployment covers practically the whole territory of the city and monitors 26 magnitudes: temperature, relative humidity, soil moisture, solar radiation, rainfall, wind speed, atmospheric pressure, acceleration, water flow, CO, particles, NO_2, ozone, bus speed, course, odometer, location, CAN, road occupancy, vehicle count, vehicle speed, presence, light, noise, authorization, and parking occupancy. There exist 7 classes of IoT devices: repeater, gateway, node, tag, mobile node (in buses), augmented reality tag, and (participatory and augmented reality) smartphones. These devices generate 305,022 observations per day, where 139,370 correspond to the environmental monitoring, 8365 to irrigation, 82,726 to mobile environmental monitoring, 13,489 to parking occupancy, 54,720 to traffic management and 6352 to participatory sensing, yielding a total of 450 MB per year. These IoT devices support reprogramming of their source code by means of OTAP (On-The-Air Programming) and Multicast OTAP. 10 communication technologies are supported: IEEE 802.15.4, IEEE 802.11 (with 150 Wi-Fi access points over the city), Digimesh, GPRS/UMTS, NFC, RFID, UART, Bluetooth, Ethernet, and proprietary communication technologies. The SmartSantander platform provides a REST interface for the publication and data access in real-time, alarms and notification management, data mining supported on the IoT nodes themselves, and OMF (cOntrol and Management Framework), a generic framework for developing and controlling networking testbeds that are written in OMF Experiment Description Language (OEDL). In 2014, SmartSantander was integrated with FIWARE, which enables the data access and to the context information of the IoT nodes via a REST Interface (GET Method) to access by position, by node and by type of sensor, and consult historic data. A catalog of open data with 87 datasets is currently available in the city website. Smart City Santander is on Facebook, Twitter, Linkedin, and

CityScripts, a social tool for SmartSantander experiments; the number of social network users in Spain reaches 22.84 million people for a population of 46.52 million inhabitants. An SDK and an API based on Arduino/Libelium are available to write mobile applications able to manage IEEE 802.15.4 communications, handle incoming packets, retrieve sensor data, and miscellanea. Thus, citizens are encouraged to develop their own apps by using both the SDK/API and the open data, and put them available to third parties by uploading the resulting apps to the website. Thus, 15 apps are currently available with a total of 19,695 downloads registered, which implies a 11.10% of its population. Pace Of the City and Service of Augmented Reality are two of the most popular applications for the users. As a member of the Group *CTN 178 Smart Cities* of the Spanish Standards Body (AENOR), Santander city council has participated in the elaboration of 15 Spanish standards on smart cities, just to cite three examples *UNE 178301 Smart Cities. Open Data*, *UNE 178303 Smart Cities. Asset management of the city. Specifications*, and *UNE-ISO 37120 Sustainable development of communities – Indicators for city services and quality of life* (ISO 37120:2014). 18 KPI (Key Performance Indicators) were identified to measure the progress: efficiency of the use of parking spaces, service management satisfaction, coverage area, availability of a city noise map, measurement quality ratio, ratio between real measurements and estimations, number of times that the maximum acoustic level is exceeded, user energy consumption, user energy wasted, user energy consumption after feedback introduction, technology engagement, volume of used water, incidents reported to the municipality services and response time, time to solve incidents, satisfaction level once the incidence is solved, user perception of application and service concepts, user perception of the design and features of the developed application. From this set of KPIs, the only available measure is the time for resolution of incidents, that descended from 38.5 days to 9.43 days on average, which implies a reduction of 75.5%.

4.2. Seoul smart city

Seoul is known as one of the most tech-savvy cities in the world. The city has progressively evolved from a model based on advanced technological infrastructure towards a model that provides citizen-centric services while sustainability and competitiveness of the city are also boosted. Seoul has embarked on 4 smart domains: metering, governance and open data, safety, and waste management, implemented through 6 main projects: smart devices for all, u-Seoul net, u-Seoul safety service, smart metering project, smart work center, and community mapping. Seoul is using 15 classes of devices: Passive RFID, Active RFID, Mobile RFID, Physical Sensor, Chemical Sensor, BioSensor, GPS device (mobile phones), IR-based technology, WLAN-based technology (RADAR, PlaceLab), Ultra-sonic waves-base technology, video-based technology (EasyLiving), Smart Cards, CCTV, smart meters, and clean cubes. At least 30,000 CTV, 1000 smart meters in households and 85 clean cubes have been installed. These IoT devices monitor 19 magnitudes: Temperature, pressure, speed, accelerometer, flow, load, radiant energy, CO, NOx, ion, humidity, blood glucose meter, cholesterol meter, GPS, location, active badge, RF signal strength received, 3D camera, bin status, that employ 12 communication technologies: optical wire, Wi-Fi (10,430 Wi-Fi hotspots installed), NFC, RFID, ZigBee, HSDPA, LTE, UMB, WiMax, Wibro, GSM, WCDMA (in clean cubes). Seoul Data Center integrates more than 1400 machines including servers, storage devices, network equipment, information security systems, and accessory facilities. The platform integrates the real-time data collected by IoT devices in a corpus of 150 databases, it supports alarms under emergency situations (e.g. heavy rain, snow, typhoons), data analytics (e.g. optimization of routes and planning decision) and security (770 cyber-attacks detected per day on average). The center has integrated a total of 44 social media accounts, as Facebook, Flickr, Instagram, Twitter, Cyworld (the most popular social network in Korea), KakaoTalk, and Line; South Korea has 26.15 million of users and a total population of 49.54 million, thus 52.78% of its population uses social networks, and more than 75% of Seoul's mobile phone users are also smart device users. Mobile Seoul website provides Seoul's citizens with 62 services over 11 types of different mobile devices. Seoul city offers 37 public applications developed by Seoul municipality or in partnership with the private sector, and Seoul's Public Application Management System monitors the number of people using each app, identifies overlaps of functionalities and ensures that the contents remain up-to-date. Mobile Seoul website receives 7,737,513 visits (monthly average). Open Data to citizens is provided through Seoul Open Data Square website that discloses public information under ten categories and offers a catalog of 880 datasets. There is available an open API for reading data and data reuse by using just URLs as web services; however, no SDK is provided to users (they may nevertheless develop applications directly on Android, Apple, etc.). Seoul is signatory of *ISO TC 268/SC 1 Smart Community infrastructures metrics*, *ITU-T Smart Sustainable Cities*, *ITU-T Study Group 5. Environment and climate change*, and *ITU's 3rd Green ICT Application Challenge for Smart Sustainable Cities* standards. 9 KPIs to measure the progress have been identified: number of employees making use of smart work, percentage of satisfied employees, percentage of employees with interest in working in the future, percentage of people that checks their consumption once per day, percentage of people that think that the program is useful, percentage of people with interest in participating in similar projects, percentage of reduction of the collection frequency, percentage of reduction of the waste collection, percentage of increase of the recycling diversion rate and number of devices donated to people in need. From this set, 3 metrics were used to compute the average improvement: reduced waste collection costs by 83%, increased recycling diversion rate to 46%, and eliminated over owing waste bins with 66% reduction in collection frequency, resulting into a 65% of improvement on average.

4.3. New York smart city

New York city focuses on 7 domains: smart infrastructure, smart transport & mobility, smart energy, smart environment, smart public health, smart safety, smart government & community, that are implemented via 10 projects: smart indoor lighting, wireless water meters, responsive traffic management, traffic signal prioritization, smart waste management, water and air quality monitoring, real-time gunshot detection, snow plow tracking, and 24/7 server requests. 15 classes of devices have been installed on the 5 boroughs: 817,000 water meters, 100 microwave sensors, 149 E-ZPass readers, 12,400 Advanced Solid-state Traffic Controllers, 60 TransCore Encompass reader sites, 210 remote traffic microwave, vehicle detector (RTMS sensors), 400 video cameras, Traffic Signal Prioritization for 300 buses, 700 BigBelly bin cubes, 967 water sampling stations, air monitoring equipment at 75 sites, 300 microphone sensors (for gunshot detection), 2550 GPS in snow plots, more than 250 smart screens, and smartphones (citizen participation). These devices are able to measure more than 38 magnitudes: bin-level detection at 75%, smell detection, individual water consumption, water leaks, energy consumption, greenhouse gas (GHG) emissions in buildings, detect vehicle presence and monitor traffic volume and speed, travel times, congestion, location, transit vehicle detection, GPS, physical, organic and chemical parameters (e.g. alkalinity, aluminum, barium), gaseous criteria pollutants (e.g. ozone, sulfur dioxide, carbon monoxide), PM2.5, meteorological data, real-time acoustic gunshot detection, monitor vehicle progress (via GPS) and people location (via GPS in smartphones). The IoT devices use 6 communication technologies: RFID, Wi-Fi (1476 hotspots), GPS, 910–920 MHz unlicensed RF, cellular network, and GSM/GPRS. Real-time monitoring, analysis of data, and alarms management are supported (e.g. traffic speed data, traffic signal prioritization in buses, snow plow tracking). Some still smart services as for instance the gunshot detection integrate information from different sources (e.g.

acoustic sensors, license plates, video feeds, radio and chemical sensors) to make intelligent decisions on the notification of the event to New York Police Department. A local law of 2012 requires each city to identify and ultimately publish all of its digital data by 2018. The NYC Open Data website has already published 1587 datasets, which can be accessed by citizens via web or by mobile application developers via the Socrata Open Data Publisher API (based on REST) and a query language called Socrata Query Language. There are also multiple available libraries and SDKs for Android, Apple, PHP, Ruby and Java developers, among others. 55 official apps have been published at this website, *311* app being the the most popular one with 13,000 downloads per month on average; the website receives 503,305 visits monthly average. NYC Open Data is in Facebook and Twitter and the number of social network users in the country is 190.19 million. USA is a signatory of the ISO/ITU defined standards on smart cities, *ANSI Network on Smart and Sustainable Cities* and New York of Local Law 11 of 2012. To quantify the progress achieved 15 KPIs are defined: number of travels saved and cost of the saving travels, reduction of costs for manual readings, reduction of the customer billing, reduction of notifications of water leaks, improvements in travel times, reduction of vehicles idle times, reduction of transit bus delays, automatic notification of events before water arrives New York, pollution level, time of response of the system vs. times of response of calls to 911, number of arrests for illegal gun discharges, improving arrival times for emergency personnel responding to shooting scenes, deterrent effect to gun use, reduction of the calls to 311, and number of apps downloaded. From this set, an average improvement of 68.48% for the 9 available KPIs is obtained.

5. Discussion

This section presents the major outcomes of our research. First, we discuss the results obtained from the demonstrator presented in Section 4; then, we provide a critical review of the strengths and weakness of our approach.

5.1. Results from the demonstrator

The results shown in Table 7 rank New York, Santander, and Seoul with 56.93, 52.31, and 49.52 out of 100, respectively. This means that New York has the highest aggregated value of the ICT indicators proposed. It is important to note that these results should be understood in the context of the demonstration of the proposed methodology and not as final results of its application. More importantly, the outcome of this research is oriented to understand better the strengths and weakness of the smart cities of today by focusing our attention on technological aspects. Differently to other rankings, our ranking evaluates Santander better than Seoul. Compared to New York and Seoul, Santander is an example of smart city at a smaller scale. Santander is the only city that implements two appealing features for IoT, as are remote reprogramming of devices and integration with the FIWARE platform. These characteristics ensure autonomous adaptation of the device code, openness, and interoperability. In turn, Seoul reaffirms itself in the role of tech-savvy city, with the highest ratio between Wi-Fi hotspots and population and the highest percentage of social network users. However, the fact of having the largest technological infrastructure does not imply achieving the highest degree of *smartness*, as suggested in this study.

$\Omega_{i|k}$ values collected in Table 7 were directly extracted from official documents[1,2,3] published by the municipalities. This is a guarantee of their origin, quality and accuracy. New York, Seoul, and Santander are examples of transparency: not only datasets are shared but also very valuable information on how they are implementing the *smartization* process is published.

5.2. Summary of the strengths and weakness

We summarize in the following paragraphs the main strengths and weakness of the proposed methodology:

5.2.1. Strengths

- **Coherence with the most commonly accepted vision of IoT and smart cities**. Due to the fact that there is no global agreement on *what is* and *what is not* a smart city, the projects are frequently mixed under some smart category while what the understanding of the concept smart is overlooked. For instance, the amount of kilometers of bicycle lanes and the replacement of streetlights bubbles by LEDs (initiatives clearly oriented to save energy and increase the life quality) are frequently labeled as smart. Therefore, a common feature of the smart initiatives of today is the implementation of strategic plans to mitigate urban problems, where such plans do not necessarily use technology to achieve the objectives of efficiency and sustainability. However, this fact is not consistent with the most commonly accepted vision of smart city: the usage of ICT for their realization. In this sense, our ranking for evaluating smart cities is better aligned with this perspective, since it employs specific ICT indicators extracted from the enabling technologies for IoT.
  However, we also believe that not only the use of technology becomes a city smart *per se*: it is also necessary to develop strategic plans oriented to improve some aspect of the citizens quality of life, for instance, by enabling real-time data collecting and making intelligent decisions based on them. Following with the bubbles replacement example, a smart lighting strategy may dynamically adapt the LED intensity according to certain environment variables (e.g. time, climate, environment light) in order to maximize the energy savings (Escolar et al., 2014). Thus, what is more important is *what* is done with the data, *what* could be done and *which* would be the impact on the city.
- **ICT and smartness indicators**. For the purpose of determining *how* smart is a city, a set of specific ICT and smartness indicators, beyond the urban development indicators, have been proposed. This is a strength of our methodology itself, since it enables to focus on the smart city development instead of urban development, differently to other rankings.
- **Easily extensible with new indicators**. The set of indicators can be easily extended by adding new smart city-related indicators, even of different nature (e.g. human factors), to improve the accuracy of the results, and then to recompute r_{Ω_i} accordingly. To make a fair comparison, the only requirement is that all the cities considered in the evaluation should have a valid value for the new indicator.

5.2.2. Weakness

- **Subjectivity of the MADM method**. As introduced in Section 3, our MADM-based methodology is centered on the selection of a set of indicators aimed at quantifying not only the quantity of ICT resources employed in the city but also its *quality* and the smartness degree of the provided services. As far as we know, this work presents the first attempt to collect such set of indicators for ranking smart cities, since there is a lack of a set of indicators commonly accepted for this purpose. In this sense, our method is not exempt of certain subjectivity as it depends on the selected indicators. However, such subjectivity is not exclusive of our method, since the ranking elaboration process needs to select variables, build indicators, and weight them; these steps are generally implemented based on participatory methods or experts evaluation.
- **Limited number of cities involved in our ranking**, as a consequence of either a lack of transparency or unawareness of the information. It was difficult to find the values of the indicators. Moreover, if they are available, most of them are related to specific

smart initiatives and not to the overall city, so we had to aggregate them in a single value for each indicator *k*. Surprisingly, the overall information is frequently unknown even by the municipalities, due to the fact that different initiatives could be in charge of different departments and/or private companies that do not always share or publish information for the sake of protecting the intellectual property of their developments. Unfortunately, most of the cities surveyed to elaborate this work do not provide these data.

6. Conclusions

The need to be present in city rankings to gain visibility in the race to become *smart* is widely accepted. However, as investigated in this paper, smart city rankings are generally based on urban development criteria while other criteria related to the use of ICT are not incorporated (or, at least, not in depth), since technology is the driving force addressing the transformation of the cities. In this paper, the suitability of current city rankings to offer a holistic view of the smartness of a city has been questioned.

Precisely, the need of a more adequate ranking, attending to the smartness and technological level developed by cities to achieve the smart city concept, has motivated our proposal of a methodology based on MADM for designing rankings targeted to smart cities. Our ranking contemplates explicitly 38 relevant ICT indicators grouped into a transversal, smartness dimension, so that the smartness degree of the individual initiatives and of the overall smart city may be effectively measured. As far as we know, no ranking for evaluating smart cities under this perspective has been developed. We apply our methodology to a case study that considers three of the smartest cities worldwide: New York, Santander and Seoul. The results reported differ from the provided ones by the smart city rankings analyzed, which suggests a deeper analysis of current rankings and the need of including technological criteria for smart cities classification. As future work we plan to automate the process of ranking calculation. Specifically, we are working on publishing forms where the city managers may easily provide the values of the indicators and obtain as a result the score of the city among the set of cities participating in the experiment.

Acknowledgments

This work has been funded by the Programme for Research and Innovation of the University of Castilla-La Mancha, co-financed by the European Social Fund (August 25, 2014 Resolution) and by the Spanish Ministry of Economy and Competitiveness under project PLATINO (TEC2017-86722-C4-4-R) and CitiSim Itea3 (TSI-102107-2016-4).

References

Anon. Part 15.3: wireless medium access control (mac) and physical layer (phy) specifications for high rate wireless personal area networks (wpans). draft standard, IEEE 802.15.3 Working Group, Part 15.3
ZigBee Specification, 2005. zigbee document 053474r06, version 1.0 /home/jfd1/smb4k/EMC1/jfd1/group/projects/current/FLAVIIR_Wireless/Literature/Wireless_Technology/Zigbee/054024r00ZB_MG-ZigBee-Specification-v1.0-Download.pdf.Dec.
Anon, 2008-2009. Coordination and support action for global rfid-related activities and standardisation (casagras). fp7-ict-2007-1. https://cordis.europa.eu/project/rcn/85786_en.html.
Anon, 2008-2011. Wireless sensor network testbeds (wisebed). fp7-ict-2007-2 224460. http://www.wisebed.eu/.
Anon, 2009-2011. Smart objects for intelligent applications (sofia). artemis-ju call 2008 100017. http://www.sofia-project.edu.
Anon, 2010. Ecma International. (2010). ecma 352: Near Field Communication Interface and Protocol (nfcip-2). http://www.ecma-international.org/memento/TC47-M.htm.
Anon, 2011-2014. Fiware - Future Internet Core Platform. https://www.fiware.org/.
Barcelona City Council, 2012. Inside the City OS. http://ibarcelona.bcn.cat/sites/default/files/city_os_-_inside.pdf October.
Anon, 2012. International Data Corporation (idc). Smart Cities Analysis in Spain 2012-The Smart Journey. http://www.portalidc.com/resources/white_papers/IDC_Smart_City_Analysis_Spain_EN.pdf.
Anon, 2012. Siemens AG. The Green City Index. https://www.siemens.com/entry/cc/features/greencityindex_international/all/en/pdf/gci_report_summary.pdf.
Anon, 2014. Angelo Corsaro, Ph.D. Chief Technology Officer omg. Building the Internet of Things with DDS. http://www.omg.org/news/meetings/tc/nj-13/special-events/iot-pdfs/corsaro.pdf.
Anon, 2014. Open Geospatial Consortium (OGC). OGC Sensor Model Language (sensorml) 2.0 Encoding Standard. http://www.opengeospatial.org/standards/sensorml.
Anon, 2015. CityProtocol Society Task Force. City Anatomy: A Framework to Support City Governance, Evaluation and Transformation. http://www.cptf.cityprotocol.org/CPAI/CPA-I_001-v2_Anatomy.pdf November.
Anon, 2015. Human Smart Cities Network. http://www.humansmartcities.eu/.
Anon, 2015. Iese Business School. University of Navarra. Cities in Motion Index. http://www.iese.edu/research/pdfs/ST-0366-E.pdf.
Anon, 2016. Living PlanIT Introduction to the PlanIT Urban Operating *System*^{TM} Architecture. http://living-planit.com/pdf/living-planit-introduction-to-uos-architecture-whitepaper.pdf June.
Anon, 2016. Transport for London: How Big Data is Used to Improve and Manage Public Transport in London. John Wiley & Sons, Ltd, pp. 223–228. https://doi.org/10.1002/9781119278825.ch35.
Anon, 2016. Iso/iec 20922. Information Technology - Message Queuing Telemetry Transport (mqtt) v3.1.1. http://mqtt.org February.
Akyildiz, I.F., Su, W., Sankarasubramaniam, Y., Cayirci, E., 2002. A survey on sensor networks. Comm. Mag. 40 (8), 102–114.
Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., Ayyash, M., 2015. Internet of things: a survey on enabling technologies, protocols, and applications. IEEE Commun. Surv. Tutorials 17 (4), 2347–2376. https://doi.org/10.1109/COMST.2015.2444095.
Albino, V., Berardi, U., Dangelico, R.M., 2015. Smart cities: definitions, dimensions, performance, and initiatives. J. Urban Technol. 22 (1), 3–21.
Ashton, K., 2009. That “Internet of Things” Thing. RFiD J. 22, 97–114.
Atzori, L., Iera, A., Morabito, G., 2010. The internet of things: a survey. Comput. Netw. 54 (15), 2787–2805.
Enabling Things to Talk: Designing IoT Solutions with the IoT Architectural Reference Model. In: Bassi, A., Bauer, M., Fiedler, M., Kramp, T., Kranenburg, R. v., Lange, S., Meissner, S. (Eds.), Springer, Heidelberg.
Batty, M., 2013. The New Science of Cities. The MIT Press.
Bhatti, S., Carlson, J., Dai, H., Deng, J., Rose, J., Sheth, A., Shucker, B., Gruenwald, C., Torgerson, A., Han, R., 2005. MANTIS OS: an embedded multithreaded operating system for wireless micro sensor platforms. MONET 10 (4), 563–579.
Bormann, D.C., Hartke, K., Shelby, Z., 2015. The Constrained Application Protocol (CoAP). https://doi.org/10.17487/rfc7252. RFC 7252.
Brans, J., Mareschal, B., Vincke, P., 1984. Promethee: a new family of outranking methods in multicriteria analysis. In: Brans, J. (Ed.), Operational Research. IFORS 84, North Holland, Amsterdam, pp. 477–490.
Carli, R., Dotoli, M., Pellegrino, R., Ranieri, L., 2013. Measuring and managing the smartness of cities: a framework for classifying performance indicators. In: 2013 IEEE International Conference on Systems, Man, and Cybernetics, pp. 1288–1293. https://doi.org/10.1109/SMC.2013.223.
Cavada, M., Hunt, D., Rogers, C., 2014. Smart Cities: Contradicting Definitions and Unclear Measures. Proceedings of the 4th World Sustain. Forum (Session F: Sustainable Urban and Rural Development). https://doi.org/10.3390/wsf-4-f004.
Clarke, O., 2015. Smart Cities in Europe. Enabling Innovation. http://www.cleanenergypipeline.com/Resources/CE/ResearchReports/Smart%20cities%20in%20Europe.pdf.
Cohen, B., 2012. Key Components for Smart Cities. UBM's Future Cities.
Compton, M., Barnaghi, P., Bermudez, L., Garcia-Castro, R., Corcho, O., Cox, S., Graybeal, J., Hauswirth, M., Henson, C., Herzog, A., Huang, V., Janowicz, K., Kelsey, W.D., Phuoc, D.L., Lefort, L., Leggieri, M., Neuhaus, H., Nikolov, A., Page, K., Passant, A., Sheth, A., Taylor, K., 2012. The {SSN} ontology of the {W3C} semantic sensor network incubator group. Web Semant. Sci. Serv. Agents World Wide Web 17, 25–32.
de Oliveira, A.D., 2016. The Human Smart Cities Manifesto: A Global Perspective. Urban and Landscape Perspectives. Springer, Cham, pp. 197–202. https://doi.org/10.1007/978-3-319-33024-2_11.
de Santis, R., Fassana, A., Mignolli, N., Villa, A., 2014. Smart city: fact and fiction. In: Munich Personal RePEc Archive (MPRA, p. No. 54536.
Dunkels, A., Gronvall, B., Voigt, T., 2004. Contiki - A Lightweight and Flexible Operating System for Tiny Networked Sensors.
Ervural, B., Kabak, Ö., 2015. A taxonomy for multiple attribute group decision making literature. In: 2015 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), pp. 1–8. https://doi.org/10.1109/FUZZ-IEEE.2015.7338114.
Escolar, S., Carretero, J., Marinescu, M., Chessa, S., 2014. Estimating energy savings in smart street lighting by using an adaptive control system. Int. J. Distrib. Sens. Netw. 2014. https://doi.org/10.1155/2014/971587.
Fielding, R.T., Taylor, R.N., 2002. Principled design of the modern web architecture. ACM Trans. Internet Technol. 2 (2), 115–150.
Multiple criteria decision analysis: state of the art surveys. In: Figueira, J., Greco, S., Ehrgott, M. (Eds.), International Series in Operations Research & Management Science. vol. 78 Springer, New York.
Finkenzeller, K., 2003. RFID Handbook: Fundamentals and Applications in Contactless Smart Cards and Identification, 2nd ed. Wiley Publishing.
D. for Business Innovation, Skills, 2013. The *S*mart *S*ity *S*arket: Opportunities for UK. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/249423/bis-13-1217-smart-city-market-opportunties-uk.pdf October.
Giffinger, R., Fertner, C., Kramar, H., Kalasek, R., Pichler-Milanovic, N., Meijers, E., 2007. Smart Cities - Ranking of European Medium-sized Cities. Vienna University of Technology.
Giffinger, R., Gudrun, H., 2010, February, February. Smart cities ranking: an effective instrument for the positioning of the cities? In: ACE: Architecture, City and Environment, 1886-4805, pp. 7–26.

Hara, M., Nagao, T., Hannoe, S., Nakamura, J., 2016. New key performance indicators for a smart sustainable city. Sustainability 8 (3). https://doi.org/10.3390/su8030206.
Hill, J.L., 2003. System Architecture for Wireless Sensor Networks. Ph.D. thesis. University of California, Berkeley Adviser-David E. Culler.
Hoornweg, D., Nunez, F.R., Freire, M., Palugyai, N., Villaveces, M., Herrera, E.W., 2007. City Indicators: Now to Nanjing. SSRN.
Hunkeler, U., Truong, H.L., Stanford-Clark, A., 2008. Mqtt-s; a publish/subscribe protocol for wireless sensor networks. In: Communication Systems Software and Middleware and Workshops, 2008. COMSWARE 2008. 3rd International Conference on, pp. 791–798. https://doi.org/10.1109/COMSWA.2008.4554519.
Hwang, C., Yoon, K., 1981. Multiple Attribute Decision Making: Methods and Applications: A State-of-the-Art Survey, Lecture Notes in Economics and Mathematical Systems. Springer-Verlag.
Insider, B., 2014. How the 'Internet of Things' will Impact Consumers, Businesses, and Governments in 2016 and Beyond. http://www.businessinsider.com/how-the-internet-of-things-market-will-grow-2014-10.
ITU-T, 2015. Key Performance Indicators Related to the Sustainability Impacts of Information and Communication Technology in Smart Sustainable Cities. Available online: https://www.itu.int/en/ITU-T/focusgroups/ssc/Documents/website/web-fg-ssc-0269-r4-KPIs_impact.docx.
Jucevicius, R., Patasiene, I., Patašius, M., 2014. Digital Dimension of Smart City: Critical Analysis 156.
Kim, J., Lee, J., Kim, J., Yun, J., 2014. M2M service platforms: survey, issues, and enabling technologies. IEEE Commun. Surv. Tutorials 16 (1), 61–76.
Kune, R., Konugurthi, P.K., Agarwal, A., Chillarige, R.R., Buyya, R., 2016. The anatomy of big data computing. Softw. Pract. Exper. 46 (1), 79–105. https://doi.org/10.1002/spe.2374.
Lazaroiu, G.C., Roscia, M., 2012. Definition methodology for the smart cities model. Energy 47 (1), 326–332 Asia-Pacific Forum on Renewable Energy 2011.
Lehofer, M., Heiss, M., Rogenhofer, S., Weng, C.W., Sturm, M., Rusitschka, S., Dippl, S., 2016, April, April. Platforms for smart cities: connecting humans, infrastructure and industrial it. In: 2016 1st International Workshop on Science of Smart City Operations and Platforms Engineering (SCOPE - GCTC), pp. 1–6. https://doi.org/10.1109/SCOPE.2016.7515056.
Lombardi, P., Giordano, S., Farouh, H., Yousef, W., 2012. Modelling the smart city performance. Innov. Eur. J. Soc. Sci. Res. 25 (2), 137–149. https://doi.org/10.1080/13511610.2012.660325.
Nam, T., Pardo, T.A., 2011a. Conceptualizing smart city with dimensions of technology, people, and institutions. In: Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times. dg.o '11 ACM, New York, NY, USA, pp. 282–291.
Nam, T., Pardo, T.A., 2011b. Smart city as urban innovation: focusing on management, policy, and context. In: In Proceedings of the 5th International Conference on Theory and Practice of Electronic Governance (pp. 185-194), September 26–28.
O'Brien, O., 2016. Bike share map. http://bikes.oobrien.com/.
I. of Things European Research Cluster, 2015. *B*uilding the *H*yperconnected *S*ociety. *ierc* cluster *b*ook 2015. http://www.internet-of-things-research.eu/pdf/Building_the_Hyperconnected_Society_IERC_2015_Cluster_eBook_978-87-93237-98-8_P_Web.pdf.
Oliveira, A., Campolargo, M., 2015. From smart cities to human smart cities. In: 2015 48th Hawaii International Conference on System Sciences, pp. 2336–2344. https://doi.org/10.1109/HICSS.2015.281.
Oliveira, A., Campolargo, M., Martins, M., 2014. Human smart cities: a human-centric model aiming at the wellbeing and quality of life of citizens. In: eChallenges e-2014 Conference Proceedings, pp. 1–8.
Oracle, 2013. Oracle's Smart City Platform - Creating a Citywide Nervous System. Tech. rep. Oracle.
Paganelli, F., Turchi, S., Giuli, D., 2014. A web of things framework for restful applications and its experimentation in a smart city. IEEE Syst. J. PP (99), 1–12. https://doi.org/10.1109/JSYST.2014.2354835.
Pardo-Castellote, G., 2003. Omg data-distribution service: architectural overview. In: Proceedings of the 2003 IEEE Conference on Military Communications - Volume I. MILCOM'03 IEEE Computer Society, Washington, DC, USA, pp. 242–247.
Pirdashti, M., Tavana, M., Hassim, M.H., Behzadian, M., Karimi, I., 2011. A taxonomy and review of the multiple criteria decision-making literature in chemical engineering. Int. J. Multicrit. Decis. Making 1 (4), 407–467.
Project, M., 2013-2015. Open Innovation for Internet-enabled Services and Next Generation Access (NGA) in 'Smart' Cities. cip-ict-psp.2012.1.3. https://cordis.europa.eu/project/rcn/191955_en.html.
Reas, C., Fry, B., Maeda, J., 2007. Processing: A Programming Handbook for Visual Designers and Artists. The MIT Press.
Roy, B., 1991. The outranking approach and the foundations of electre methods. Theor. Decis. 31 (1), 49–73. https://doi.org/10.1007/BF00134132.
Saaty, T., 1996. Decision Making with Dependence and Feedback The Analytic Network Process. RWS Publications, Pittsburgh.
Saaty, T.L., 1980. The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation. McGraw-Hill International Book Co., New York; London. http://www.worldcat.org/search?qt=worldcat_org_all&q=0070543712.
Saint-Andre, P., 2011. Extensible Messaging and Presence Protocol (xmpp): Core, RFC 6120. RFC Editor March.
Schneider, J., Kamiya, T., 2008. Efficient xml Interchange (exi) Format 1.0. Working Draft WD-exi-20080919. World Wide Web Consortium September.
Shi, H., Tsai, S.-B., Lin, X., Zhang, T., 2018. How to evaluate smart cities' construction? a comparison of Chinese smart city evaluation methods based on PSF. Sustainability 10 (1). https://doi.org/10.3390/su10010037.
Somarriba, N., Pena, B., 2009. Synthetic indicators of quality of life in Europe. Soc. Indic. Res. Int. Interdisciplinary J. Qual. Life Meas. 94 (1), 115–133.
Sornin, N., Luis, M., Eirich, T., Kramp, T., 2015. LoRaWAN Specification v1.0. https://www.lora-alliance.org/portals/0/specs/LoRaWAN%20Specification%201R0.pdf January.
Standard, O. Oasis advanced message queuing protocol (amqp) version 1.0., 2012. http://docs.oasis-open.org/amqp/core/v1.0/os/amqp-core-complete-v1.0-os.pdf.
Susanne Dirks, M.K., Dencik, J., 2009. How Smart is your City? Helping Cities Measure Progress. tp://www.asq-qm.org/resourcesmodule/download_resource/id/402/src/$@$random4bb253ffcdfcd/.
Thubert, P., Hui, J., 2015. Compression Format for IPv6 Datagrams over IEEE 802.15.4-Based Networks, RFC 6282. https://doi.org/10.17487/rfc6282.
Weiser, M., Brown, J.S., 1996. Designing calm technology. Powergrid J. 1.
Welbourne, E., Battle, L., Cole, G., Gould, K., Rector, K., Raymer, S., Balazinska, M., Borriello, G., 2009. Building the internet of things using rfid: The rfid ecosystem experience. IEEE Internet Comput. 13 (3), 48–55. https://doi.org/10.1109/MIC.2009.52.
Yin, C., Xiong, Z., Chen, H., Wang, J., Cooper, D., David, B., 2015. A literature survey on smart cities. Sci. China Inf. Sci. 58 (10), 1–18. https://doi.org/10.1007/s11432-015-5397-4.
Zanakis, S.H., Solomon, A., Wishart, N., Dublish, S., 1998. Multi-attribute decision making: A simulation comparison of select methods. Eur. J. Oper. Res. 107 (3), 507–529. https://doi.org/10.1016/S0377-2217(97)00147-1.
Zanella, A., Bui, N., Castellani, A., Vangelista, L., Zorzi, M., 2014. Internet of things for smart cities. IEEE Internet Things J. 1 (1), 22–32. https://doi.org/10.1109/JIOT.2014.2306328.
Zavadskas, E.K., Turskis, Z., Kildiene, S., 2014. State of art surveys of overviews on MCDM/MADM methods. Technol. Econ. Dev. Econ. 20 (1), 165–179. https://doi.org/10.3846/20294913.2014.892037.

Soledad Escolar received her BSc and MsC degrees from University Carlos III of Madrid (Spain) in 2001 and 2004, respectively and in 2010 her PhD degree in Computer Science. During the period between 2004 and 2014 she has been a teaching assistant and researcher at the same university. Currently she is a posdoctoral researcher at Department of Information Technologies and Systems within University of Castilla-La Mancha, Ciudad Real, Spain. Her primary research interests are mainly focused on Wireless Sensor Networks, highlighting energy management algorithms, network protocols, adaptive behavior, Internet of Things and Smart Cities.