Smart Cities Approaches for Environmental Sustainability Strategic Planning

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Abstract
The purpose of Environmental Sustainability Strategic Planning (ESSP) for a specific city is to identify goals, actions, and the ESSP matrix that defines priority actions and an estimated timeframe for implementation that will assist the city to achieve the environmental vision of the community to help mitigate climate change and preserve natural resources. Smart cities approaches include various applications of Planning Support Systems used in spatial and environmental planning and management. Data Mining as a computer-based technique is introduced in this paper as one of the smart cities approaches to be utilized for coping with this challenge of complex planning, management and decision-making processes required for conducting environmental sustainability strategic planning. This paper articulates the dimensions of ESSP, and presents the roles of Data Mining and Decision Support Systems and their use in environmental planning. The paper illustrates with examples how Data Mining and Intelligent Decision Support Systems as approaches of smart cities can be used to inform, support, and augment the processes of Environmental Sustainability Strategic Planning. This is to better equip decision makers and planners in developing efficient and reliable Environmental Sustainability Strategic Plans for their cities.
Keywords: Environmental Planning, Sustainability, Strategic Planning, Data Mining, and Decision Support Systems, Smart Cities Approaches

1. Introduction

It is essential to achieve all the three pillars of sustainability (social sustainability, environmental sustainability, and economic sustainability) in order to successfully solve the complete sustainability problem. Environmental Sustainability is considered to be the most important pillar to be obtained because the other two pillars are dependent on the greater system that people live within, the environment. The Systems Thinking seems to be an appropriate approach for realizing the relationships among the pillars of sustainability, wherein they can be viewed as a collection of interconnected systems. The largest of these three systems is the environment within which the social and economic systems function and operate bindingly to increase the general welfare of people. Observing the three pillars of sustainability from the perspective of systems thinking "*makes it clear that environmental sustainability must have the highest priority, because the lower the carrying capacity of the environment, the lower the common good delivered by the social system and the less output the economic system can produce*" (THWINK, 2019).

Environmental sustainability is an integral to and a key pillar of sustainable development of resilient and smart cities. Environmental sustainability is "the ability to maintain things or qualities that are valued in the physical environment" (Sutton, 2004). All scales of the physical environments can be considered including micro, local, global and larger scales. The urban environment of cities is composed of land, water, atmosphere, physical resources and buildings, roads and other physical elements. Environmental sustainability in smart cities requires making decisions and taking actions in order to preserve its capability to support human life, protect natural world, and reduce negative impact on the environment. It is not simply about reducing the amount of waste or using less energy, but it is concerned with developing processes that will lead cities to becoming completely sustainable in the future. Nevertheless, environmental sustainability programs include adoption of recycling, reduction of using physical resources, utilization of renewable resources, elimination of producing toxic materials in products, protection of natural habitats, and restoration of valuable environments. Environmental sustainability problems are posed by major issues including:

- living environments of native species are destructed
- polluting chemicals and other materials are discharged into the environment
- climate change caused by the emission of greenhouses gases into the atmosphere
- low cost oil and other fossil fuels are majorly depleted

Elaborating the environmental sustainability in smart cities can be achieved through creating an anticipatory adaptive management system that addresses the following issues:

- preferred conditions required to be achieved by cities
- current states of cities
- road map for the cities to get there from their current states with the least loss along the way
- identification of actions to be quickly conducted by cities

Accordingly, there is a need for a system that will anticipate expected outcomes based on current trends and will also forecast the desirable future state. The adaptability of the system then relates to the success or failure experienced in trying to create a preferred future as well as forecasting from current reality. Therefore, it is required to view environmental sustainability in smart cities from the strategic planning perspective. Organizing the present on the basis of the projections of the desired future can be conducted through the application of strategic planning. The road map that helps in leading from where a city is now to where it would like to be in a specific future is part of the strategic plan. The identification of processes of actions for achieving the mission is an integral part of strategic planning (Cassidy, 2006).

Therefore, Environmental Sustainability Strategic Planning (ESSP) is quite a complex issue especially socio-economic factors and participation of stakeholders are required to be integrated in the planning processes. Such integration is a necessity to obtain the goals of sustainable development. The important questions in this paper are what and how computer-based tools (e.g. Decision Support Systems - DSS) can be utilized to cope with the complexity of planning, management and decision making processes of environmental sustainability strategic planning.

2. Environmental Sustainability Strategic Planning of Smart Cities

The purpose of a smart city Environmental Sustainability Strategic Plan is to define a strategy that consists of measurable goals, objectives, and actions that will help the city to coordinate efforts to achieve the environmental vision of the community. Additionally, it will provide a framework for the municipality, partners, businesses, residents, and guests to take action to reduce the city's impact on global climate change and work toward a sustainable future.

New approaches of working in economic, social and political life and essential structural changes are required for achieving sustainable development. Setting goals and identifying means of achieving them are essential elements of being strategic in sustainable development. The vision must be based on solid evidence and should be reflected while setting priorities, direction and tactics for achieving the desired goals. The analysis of key challenges and their underlying causes is a necessity for developing strategies with actual or potential short and long term impacts. It is also important while identifying options for policy and institutional reforms to conduct careful analysis of links between local and national levels, and between national and global concerns. The effective communication with stakeholders is the backbone of achieving successful reforms. For instance, the integration of environmental and social analysis in strategic planning processes presents opportunities for improving the sustainability and coherence of development plans and policies and encourages the consideration of long term implications (OECD, 2001).

The Emerging and Sustainable Cities Initiative (ESCI) represents a new approach dealing with the most urgent challenges of the city. It uses an integrated and interdisciplinary perspective, which is necessary for identifying the path to long-term sustainability. In general, the ESCI methodology includes the four phases (as shown in Figure 1), consists of a rapid evaluation of the urban reality and ends with the preparation of an Action Plan for the city's sustainability, containing specific proposals for intervening in the areas identified as critical. The process starts by identifying the most urgent challenges to the city's sustainability, through a rapid evaluation based on: (i) a quantitative analysis, using approximately 120 indicators obtained mainly from secondary information (as shown in Table 1; (ii) a technical and qualitative analysis, based on the deep knowledge of specialists and technicians experienced in the sectoral topics of the Initiative; and (iii) baseline studies, which include maps of vulnerability to natural disasters and the effects of climate change, studies of urban growth, and an inventory of the effect of greenhouse gases (GHG). As a supplement, based on the city's situation, additional baseline studies are included, which can cover topics such as fiscal management, citizen security, transport (motorized and non-motorized), water and sanitation, and solid waste, among others (Juan et. al., 2014).

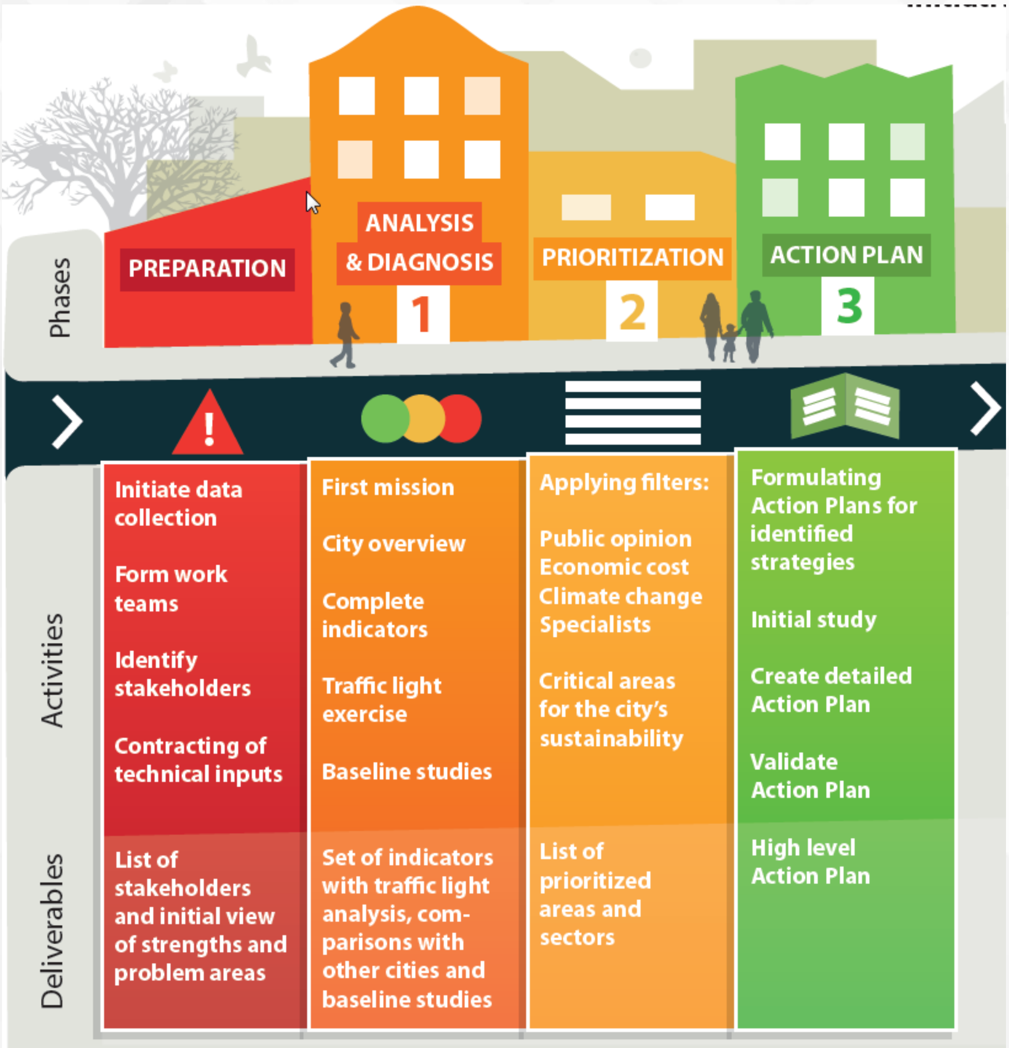

Figure 1: The four phases of the Emerging and Sustainable Cities Initiative (ESCI) (adopted from Juan et. al., 2014).

3. Big Data and Data Mining for Environmental Sustainability of Smart Cities

Modern living seems to be the first choice in urban smart cities while more than half of the population around the world is living in urban environments (Vilajosana et al, 2013). Accordingly, smart cities are facing more costs on labor, transportation, infrastructures, energy, and many other basic needs. Cities consume more energy to fuel their day-to-day activities. With the rise of electrical devices more challenges are faced and associated with energy control and distribution. This is in addition to spending a lot of energy for either heating or cooling (Costa and Santos, 2015). Furthermore, citizens are behaving like natural consumers of city services and are now demanding more, regardless of the existing constraints (Hedlund, 2011). Consequently, vast amounts of data with multiple degrees of complexity are continuously generated by cities and their citizens at different speeds and from various sources. Herein is where Big Data comes along.

Table 1: Dimensions, Pillars, Topics and Indicators of the Emerging and Sustainable Cities Initiative (ESCI) (Juan et. al., 2014)

Dimension	Pillar	Topic	Number of indicators	Indicator example (unit of measurement)
Environmental Sustainability and climate change	Management of the environment and consumption of natural resources	Water	6	Continuity of water service (hours/ day)
		Sanitation and drainage	3	Households with a home connection to the sewer system (percentage)
		Management of solid waste	7	Remaining life of the site where the landfill is located (years)
		Energy	8	Average length of electrical interruptions (hours/customer)
	Mitigation of greenhouse gases (GHG) and other forms of pollution	Air quality	3	Air quality index (number)
		Mitigation of Climate change	4	Existence and monitoring of GHG Inventory (Yes/No)
		Noise compliance	1	Existence, monitoring and enforcement of regulations on noise pollution (Yes/No)
	Reduction of vulnerability to natural disasters and adaptation to climate change	Vulnerability to natural disasters in the context of climate change	8	Critical infrastructure at risk due to inadequate construction or placement in areas of non-mitigable risk (percentage)
Urban sustainability	Control of growth and improvement of human habitat	Land use, Planning, and zone	8	Quantitative housing deficit
		Urban inequality	3	Percentage of housing located in informal settlements (percentage)
	Promotion of sustainable urban transport	Mobility and transport	12	Average age of the public transport fleet (years)
	Promotion of competitive and sustainable local economic development	Competitiveness of the economy	3	Days to obtain a business license (number of days)
		Employment	2	Average annual unemployment rate (percentage)
		Connectivity	3	Fixed broadband Internet subscriptions (number of subscriptions for every 100 inhabitants)
	Provision of high-level social services and promotion of social cohesion	Education	9	Student/teacher ratio (students/ teachers)
		Security	7	Victimization rate (percentage)
		Health	6	Life expectancy at birth (years)
Fiscal sustainability and governability	Adequate mechanisms of government	Participatory public management	3	Public reporting sessions per year (number)
		Modern public management	4	Existence of a multi-annual budget (Yes/No and years)
		Transparency	3	Municipal government accounts audited (percentage)
	Adequate management of revenue	Taxes and financial autonomy	6	Utility cost recovery (percentage)
	Adequate management of expenditure	Expenditure Management	5	Gross Capital budget (capital expenditure as percentage of Total expenditures)
	Adequate management of debt and fiscal obligations	Debt	3	Contingent liabilities as percentage of own revenue (percentage)

The ability of society in harnessing information and producing useful insights or goods and services of significant value in novel ways is referred broadly as the Big Data (Mayer-Schönberger and Cukier, 2013). A concrete definition of Big Data has yet to be formulated regardless of its continuing increase in popularity (Dumbill, 2013). A popular definition of Big Data encompasses the volume, velocity, and variety of data (Laney, 2001). The increased amount of data to be managed, the increased pace of data generation, use and interaction, and the many and often incompatible data formats, structures, and semantics refers to volume, velocity, and variety respectively. Additional dimensions are recently included such as veracity, visualisation, and value (Sowe and Zettsu, 2014). Big Data has also been defined as, "datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyse" (Keeso, 2014). One of the most important developments to revolutionising environmental sustainability is the emergence of the circular economy. It entails a critical shift from the classic linear approach that discards waste and often focuses on creation and use. A central role to be played in conjunction with the digital revolution is through the application of Big Data.

Extracting helpful and needed patterns from large repositories of data is an important outcome of using Data Mining and is considered as a transformation of data to information and ultimately to knowledge. Whenever there are situations and scenarios with huge data volumes that exceed any individual's investigative capabilities Data Mining techniques can be best utilized and implemented. There are several early methods for the extraction and identification of patterns such as the Bayes' theorem and the regression analysis. In the digital revolution, data storage has grown in size to unthinkable ranges that only computerized methods can be applied to find patterns among these large repositories of data. Data Mining techniques such as clustering, decision trees, neural networks and support vector machines, and genetic algorithms are used to discover and uncover hidden patterns within data (Al-Zegaier et al, 2011).

Big Data and the possibilities it brings provides the capability to process data from a city and demonstrate and provide intelligent services both for citizens and for the government or other stakeholders, through the use of data mining techniques such as clustering and time series forecasting (Gama, 2010). For instance, clustering can be used to identify groups of homogeneous homes, with similar patterns in terms of energy consumption, enabling comparison and ranking, while time series forecasting is used to foresee future consumptions. The notion of Big Data and its potential utilization in ecosystem and human activities through supporting the development of regenerative human settlements is addressed by Kamrowska-Zaluska and Obracht-Prondzynska (2018). They assessed the possibilities created by Big Data-based tools in supporting regenerative design and planning and the role they can play in urban projects. Furthermore, Allam et al (2019) addressed the need to expand using Big Data beyond infrastructure to include urban health. The provision of cohesive set of data can lead to a better knowledge on relationships of people with the city and how this pertains to the thematic of urban health. This will be useful towards the pursuit of more contextualized, resilient, and sustainable smart cities, rendering more liveable fabrics, as outlined in the Sustainable Development Goal (SDG) 11 and the New Urban Agenda.

4. Data Mining Tools and Applications in Environmental Sustainability of Smart Cities

There are various data mining tools that can be useful for environmental sustainability of smart cities. Some of these tools are commercial packages that can provide general decision support in a certain environmental areas such as forest fighting or waste water treatment plants. Giberta et al (2012) introduced in detail commercial data mining software packages including: SAS Enterprise Miner; IBM SPSS Modeller (formerly Clementine); Salford Systems Predictive Modeling Mining Suite (SPM); Angoss Knowledge Studio; DBMiner; and GhostMiner. This is in addition to some of free software data mining packages including: Rapid Miner; Weka; KNIME (Konstanz Information Miner); The Algorithm Development and Mining System (ADaM); GESCONDA: Intelligent Data Analysis System developed for facilitating knowledge discovery and geared towards environmental databases. Most of Data Mining tools provide graphical user interface. Also, some of them allow saving the workflow and retrieve it in future sessions to be repeatedly executed with new data. GESCONDA includes a methodological recommender that helps users in selecting environmental goals that Data Mining methods can be used for investigating the relevant patterns corresponding to these goals. SAS Enterprise Miner and GESCONDA provide the possibility to reuse the results of a certain Data Mining which allows reusing the mined knowledge for further data mining to facilitate powerful analysis. Some of the applications of using Data Mining in environmental sustainability are presented in the following subsections.

4.1 Using Data Mining for Forecasting Energy Consumption

There are available approaches to forecast energy consumption, some of which are mainly related with the energy price (Zhou et al, 2011), energy loads (Alzate and Sinn, 2013). The common practice around these works seems to be the mining of clusters before applying forecasting models. Alzate and Sinn (2013) have achieved a 20% improvement in forecasting accuracy, using clustering before applying a forecaster. Regardless of the used clustering techniques, such as KMeans, Subtractive Clustering, Kernel Spectral Clustering or Partial Clustering, as well as forecasting techniques, such as Neural Networks, Support Vector Machines, Adaptive Neuro-Fuzzy Inference System or Fuzzy Inference, there seems to be a general common approach: use of clustering to improve efficiency of the forecasting model, either by adapting a model for each cluster or by using clustering as a feature extraction technique. However, there is a need for not only focusing on the data mining process and results, but also on the nature of the real world data that requires new storage and processing technologies and the importance of the possible technological deployment, in order to deliver new services to citizens (Costa and Santos, 2015).

4.2 Using Data Mining for Life Cycle Assessment

In order to appropriately conduct the assessment of environmental impacts there is need to create vast databases that contain detailed lists of products, components and processes with specific environmental impact factors attached to the entries in these lists. The methodology used to quantify the multiple environmental impacts of a product across its entire life cycle from creation, use to recycle is called the Life cycle assessment (LCA). The inventory tree is considered to be the key object of interest in LCA. It refers to the desired product as the root node and the materials and processes used across its life cycle as the children. In any environmental category, the total impact is a linear combination of the impacts of the children in that category. The following two use cases are important for realizing the usefulness of automated discovery of LCA. First case is the assessment validation: manufacturers may put carbon labels (the impact factors) on their products, but not necessarily publish any underlying information. There is no method in the field exists to validate the claims other than elaboration and expensive manual audits. Hence, discovering the LCA trees could determine whether the disclosures are reasonable. Second case is the sustainable re-design: it is expensive and time consuming for a supplier to estimate the impact of a product (parent) based on all its children, so a node in the impacts database approximately equivalent to the parent (root) is selected and the footprint computed without knowledge of its LCA tree. While this provides a total footprint of the parent, it does not give any insight into a "hotspot" analysis, i.e., which components and processes (children) are the most significant contributors to the total footprint; such information that can be vital in improving the sustainability of the product. Sundaravaradan et al (2011) proposed a data mining approach to solve the inverse problem, where the task is to infer inventory trees from a database of environmental factors. This is an important problem with applications in not just understanding what parts and processes constitute a product but also in designing and developing more sustainable alternatives.

5. The Data Mining Approach for Environmental Sustainability Strategic Planning of Smart Cities

The purpose of the Environmental Sustainability Strategic Plan of a city is to define a strategy that consists of measurable goals, objectives, and actions that will help the city coordinate efforts to achieve the environmental vision of the community. Additionally, it will provide a framework for the municipality, partners, businesses, full- and part-time residents, and guests to take action to reduce the city's impact on global climate change and work toward a sustainable future. The city will manage the environmental sustainability program outlined in this plan with cooperation among stakeholders. The Environmental Sustainability Strategic Plan is manifested in an implementation matrix that articulates goals, objectives, action items, environmental indicators, priority and resources. An excerpt of an example of an Environmental Sustainability Strategic Plan of the city of Town of Vail is illustrated in Table 2.

The sophisticated nature and complexity of developing an Environmental Sustainability Strategic Plan of a city requires tools that provide users with reasoning capabilities, support management of implicit knowledge from databases, and perform intelligent data analysis while focusing on heterogeneous data in environmental databases and environmental modelling. Such tools should help in solving predictive tasks using the obtained knowledge and in obtaining valid new knowledge to better support the decision making process. Even though with the existence of commercial systems for knowledge discovery, there is little integration of statistical and machine learning methods together or the problem solving and predictive skills in the same tool. In addition to that Knowledge Bases or Case Bases have no possibility of explicit management of the produced knowledge. The Intelligent Decision Support System (IDSS) offers complex systems that include several components: data interpretation level, diagnosis step, decision support step, strategy planning level and actuation step. Some of the most important ones are the data monitoring and data analysis modules (which include data-driven models) (Sànchez-Marrè et al, 2010).

Table 2: An excerpt of an example of an Environmental Sustainability Strategic Plan of the city of Town of Vail (ToV, 2009).

GOAL	OBJECTIVES	ACTION ITEMS	ENVIRONMENTAL INDICATORS	PRIORITY (A=High)	RESOURCES
Goal #2: Reduce the Town of Vail municipal and community energy use by 20% below 2006 levels by 2020, in order to effectively reduce the Town's contribution to greenhouse gas emissions (GHG) and impact on global climate change.	1. Track and reduce the Town of Vail municipal and community energy use and GHG emissions.	1.1 Track municipal energy use using Energy Tracker software. 1.2 Conduct community-wide GHG emissions inventory to establish baseline. 1.3 Join ICLEI's Local Governments for Sustainability Cities for Climate Protection Campaign, committing to reducing GHG emissions and achieving the "5 milestones" identified in the agreement: 1. Conduct a baseline emissions inventory. 2. Adopt an emissions reduction target for the forecast year. 3. Develop a Local Action Plan. 4. Implement policies and measures. 5. Monitor and verify results.	• GHG emissions inventory (community, TOV) • TOV energy bills (fuel, electricity, natural gas)	A - Q1 2009	Env. Team Staff Time, software, consulting fees $6,000 (est.)
	2. Implement a sustainable building code program that requires new construction and major renovations to achieve designated resource and energy efficiency targets.	2.1 Implement a high performance building code or program for all new development and Town facilities (e.g. LEED for New Construction, Green Built Colorado, or similar program). 2.2 Develop and adopt energy and resource-efficient building standards for all existing Town facilities. 2.2.1 Require all Town-funded remodel projects to exceed the International Energy Conservation Code by at least 15% on retrofits. 2.2.2 Require Energy Star or better products when available for all new equipment. 2.2.3 Utilize strategic tree planting to reduce cooling loads of buildings. 2.3 Educate the public on the adopted green building program and provide information and services at the Department of Community Development.		A - Q1 2009 - Q3 2009	Building and Env. Team Staff Time, stakeholder involvement, promotion and materials. Training for employees $30,000 (est.).
	3. Implement energy efficiency and conservation measures for municipal facilities.	3.1 Work with the Town Facilities Team to instill a culture of conservation. 3.2 Contract for an 'investment-grade' audit for all facilities that perform 20% or more below the national average, as identified in Table 2. 3.3 Obtain a performance contract for Town-owned buildings through an energy service contractor if appropriate, or invest in upgrades with reasonable payback periods, particularly the Vail Village Parking Structure, Vail Transportation Center and the Vail Public Library. 3.4 Educate Town staff and the community on global warming impacts. 3.5 Conduct feasibility study of a biomass heat and power plant in the Town of Vail using beetle killed trees, waste wood and landfill waste to offset streetscape natural gas requirements. 3.6 Research additional alternative energy options, such as solar, micro-hydro, geothermal, and wind power generated for municipal facilities. 3.7 Require life cycle cost analysis for all major equipment purchases and replacement. 3.8 Facilitate the replacement of outdated HVAC systems and other outdated equipment. 3.9 Promote the consideration of the energy and global warming pollution trade-off of new facilities and additional streetscape by evaluating impacts and providing analysis to the Town Council and management.			Env. Team Staff Time, software, consulting fees $6,000 (est.)

The integration of expert knowledge stored by human experts through years of experience, for instance in the environmental process operation and management, can be made through the use of Intelligent Environmental Decision Support Systems (IEDSS). Also, some knowledge can be acquired through the application of intelligent analysis on large databases with historical operation of environmental processes. Accordingly, Data Mining, knowledge acquisition and reasoning over the acquired models are key steps to develop reliable IEDSS. This exemplifies the strong link between Data Mining and IEDSS. IEDSS can be developed by integrating various methods of artificial intelligence, mathematical or statistical techniques, geographical information system components, and environmental ontologies with economic components. AI techniques such as qualitative reasoning, rule-based reasoning, case-based reasoning, model-based reasoning, fuzzy models, artificial neural networks, genetic algorithms, Bayesian networks, and multi-agent systems provide a solid basis for the construction of reliable and real applications. Sànchez-Marrè et al (2010) evolved GESCONDA to an Intelligent Decision Support System wherein two new functionalities were included: a case-based reasoning engine and a rule-based reasoning. These new skills of GESCONDA makes it a suitable prototype tool for the deployment of Intelligent Decision Support Systems, including all main steps like data preparation and filtering, data mining, model validation, reasoning abilities to generate solutions, and predictive models to support final users. The framework of evolved GESCONDA to an Intelligent Environmental Decision Support System is shown in Figure 2.

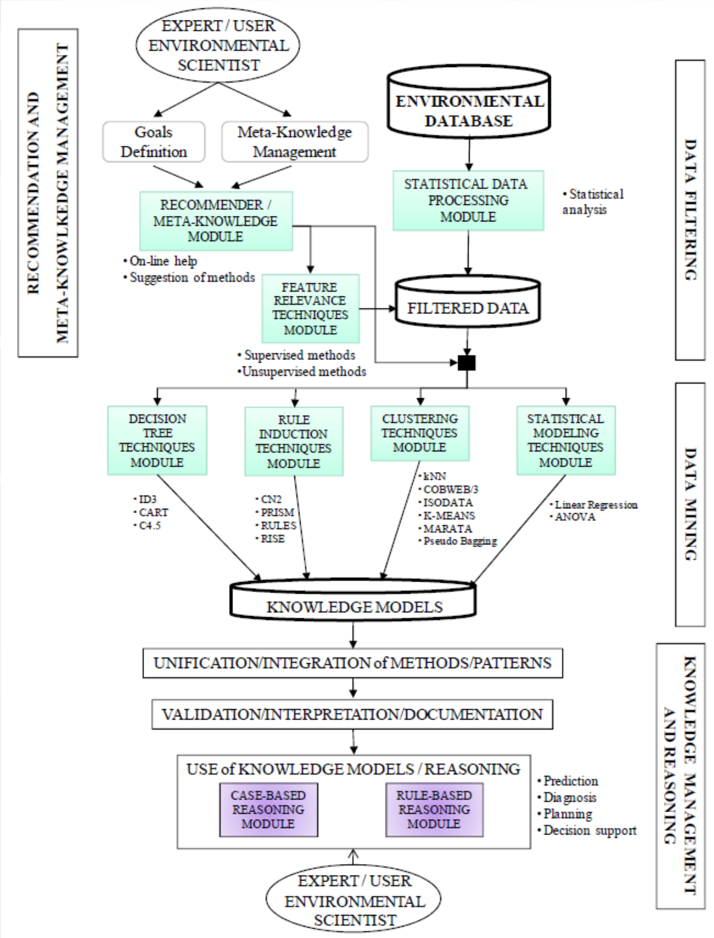

Figure 2: The framework of evolved GESCONDA to an Intelligent Environmental Decision Support System (Sànchez-Marrè et al, 2010).

6. Examples of Using Big Data Application at Local Planning Levels of Cities

This section presents some real-life examples that illustrate how Big Data is best utilized at the local planning levels and accordingly can be utilized in our cities. Urban planning requires data such as land use, locations of where people live and congregate and when, as well as their mobility, economic conditions, and where they spend their money, in additions to the locations of their social networks. The analysis of urban and regional planning involves the use of a wide range of approaches to understand and manage complex sectors, such as transportation, environment, health, housing, the built environment, and the economy. Developing approaches to improve urban operations and management; long-range plan making, and impact assessments of urban policy can be obtained through better understanding of infrastructure, physical and socioeconomic systems in cities. The developments with urban Big Data have opened up several opportunities for urban analysis including exploration and understanding of urban patterns and processes, as well as analyzing, visualizing, understanding, and interpreting structured and unstructured urban Big Data for four primary objectives (Thakuriah et al, 2015):

- ***Dynamic Resource Management**: developing strategies for managing scarce urban resources effectively and efficiently and often making decisions in real-time regarding competitive use of resources.*

- ***Knowledge Discovery and Understanding**: discovering patterns in, and relationships among urban processes, and developing explanations for such trends.*

- ***Urban Engagement and Civic Participation**: developing practices, technologies and other processes needed for an informed citizenry and for their effective involvement in social and civic life of cities.*

- ***Urban Planning and Policy Analysis**: developing robust approaches for urban planning, service delivery, policy evaluation and reform, as well as for the infrastructure and urban design decisions.*

Given the broad scope of data that can be gathered and the diversity of analytical tools and techniques available at the disposal of urban planners and policymakers, there is a seemingly limitless range of applications for Big Data in cities (Ahmed, 2018). Big data can provide new insights into longstanding problems, such as those of urban form, transport modal choices, the housing market, and labor mobility. It can also provide the ability to conduct new forms of empirical research and implement projects at new scales (Thakuriah et al, 2017). As an example, Planning support systems (PSS) offer specific tools utilizing Big Data that have received great interest over the years. One example of a PSS is "What If?" as shown in Figure 3, a GIS-based online system that is currently used in many countries. The Online "What If?" PSS tool has been designed to assist cities and regions in understanding land use supply, demand and likely future land use change scenarios. It can be used to inform strategic planners on the impact of population growth and other socio-economic factors on the future of cities. These PSS require a number of GIS data inputs including: land parcel boundaries, land uses, building footprints, demographic and economic trends, and so on. These inputs are also required to determine the suitability of land for accommodating future development – another important consideration for strategic planners in local authorities and government agencies (City planner, 2019).

Furthermore, Seoul government has been working on is the use of Big Data to improve the provision of services. An example of a Big Data project is the planning of leisure and welfare facilities for the elderly. Data on citizens over 60 was analysed by gender, district, income levels, and the use of existing leisure and welfare facilities to help the city determine which facilities should be built and where, in order to maximise their use. Another example, to ensure bus routes are chosen to maximise impact (Yimin et al, 2016), the Seoul government analysed 3 billion late-night phone calls and identified areas of activity based on phone call volume as illustrated in Figure 4.

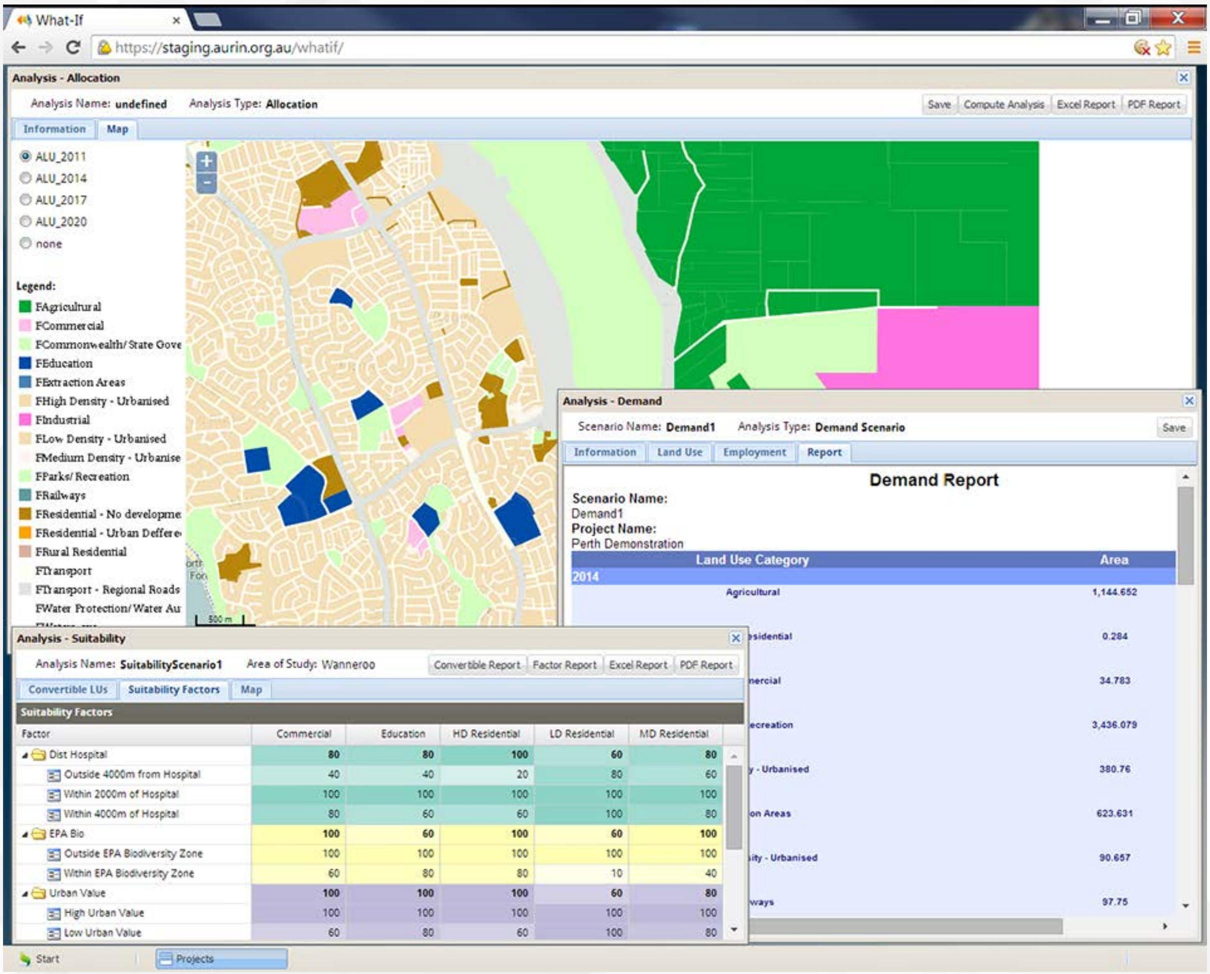

Figure 3: An example of using "What If?" to assist cities and regions in understanding land use supply, demand and likely future land use change scenarios (City planner, 2019).

Figure 4: Using Big Data, including an analysis of 3 billion late-night phone calls, the Seoul government identified 9 night bus routes that would achieve maximum impact (Yimin et al, 2016).

On the other hand, Local Planning Departments often use transportation data sets to understand traffic patterns, bike and rideshare lane use, and preferences for walking. Citizens and companies can use crowd-sourced transportation data aggregated from mobile devices to navigate real time traffic situations. There are various applications that incorporate interactive mobile data with mapping software, creating platforms that are modified and maintained by application users. Table 3 shows examples of mobility applications that use Big Data and encourage alternative transportation methods and community planning.

Table 3: Examples of applications that use Big Data and encourage alternative transportation methods and community planning (adopted from Chowdhury et al, 2018)

Category	Problem, Barriers and Desired Outcome	Sample Application Providers	Data Analysis
Planning	Transportation planning is hard in an already built environment. What to use so people can visualize the realities of the situation and help with realistic solutions?	• TransportAPI: London, UK • Waze: used everywhere by community members • Transmix: Seattle, WA • Transitlabs: GA DOT • Transit Screen: Washington, D.C.; San Francisco, CA • TransitApp: Ann Arbor, MI, Atlanta, GA	Data is often crowd sourced and almost always visualized with a mapping software
Parking	People circle downtown looking for parking. How to reduce trip time and so reduce vehicle emissions?	• ParkMe: New York. NY; Los Angeles, CA; Washington, D.C.; Austin, TX	Visually shows open parking stations
Buildings Development Planning	People want to be engaged and consulted on how their community develops. How to streamline this process so new and re-development is open and understandable?	• Civic Insight: Palo Alto, CA; New Orleans, LA • Community PlanIt: individuals and use this service anywhere • Our Common Place: available anywhere to community users • OpenStreetMap: London, UK • Mapbox: Available anywhere with fee	

Urban Big Data are gathered from a number of different sources that are classified based on typical user communities that include (Thakuriah et al, 2017):

- Infrastructure-based sensors, such as water usage, smart grids, and automotive sensors.
- User-generated content and social sensors, including social media, self-quantified data produced from wearable technology and smart-phone trackers, and participatory sensing systems.
- Government administrative data, including open data such as property tax and transit records, and confidential micro-data such as social, health and education records.
- Private sector data from both business-to-consumer as well as business-to-business perspectives, such as transaction records, customer profiles, and operational and management records such as factory production levels and stock trading data.
- Arts and humanities data, such as images, music, other media and cultural products.
- Hybrid data, such as census and survey data produced by government statistical bodies as well as private research firms.

7. Discussion: Challenges in Using Big Data for as an Approach for Smart Cities Planning

However, it should be noted that there is a distinction between the computational technologies that are commonly being used in planning such as remote sensing and GIS tools and the Big Data applications used for analyzing past performance, forecasting future needs, optimizing operations, and facilitating management. The New Urban Agenda and United Nations Sustainable Development Goals also link the data revolution to development practice and urban planning in the global South. The Urban Sustainable Development Goal (USDG) emphasizes the use of data, measurement and metrics, highlighting a notion that there are elements of urbanism that can be standardized (Ahmed, 2018).

The challenges associated with the use of Big Data for smart cities planning are: technological, methodological, epistemological, and due to political economy that arise from accessing and using the data as depicted by Thakuriah et al (2015). Technological challenges arise due to the need to generate, capture, manage, process, disseminate and discover urban information. These challenges include managing large volumes of structured and unstructured information. Other considerations include hardware, software, well-defined Application Programming Interfaces (API) needed to capture, integrate, organize, search and query and analyze the data. Of equal importance are scalability, fault-tolerance, and efficiency, and platforms for scalable execution. Various Big Data solutions have emerged in the market such as Hadoop, MapReduce and others, some of which are open source. Methodological challenges include data preparation methods (such as cleaning, retrieving, linking, and other actions needed to prepare data for the end-user) and empirical urban analysis methods (data analytics for knowledge discovery and empirical applications). The epistemological challenges pertain to the potential for insights and hypothesis generation about urban dynamics and processes, as well as validity of the approaches used, and the limits to knowledge discovery about urban systems derived from a data focus. Urban Big Data is also now being strongly associated with Open Data that is increasingly linked to smart cities. The political economy of Big Data arises due to the agendas and actions of the institutions, stakeholders and processes involved with the data. The economic, legal and procedural issues that relate to data access and governance are non-trivial and despite the current rhetoric around the open data movement, vast collections of data that are useful for urban analysis are locked away in a mix of legacy and silo systems owned and operated by individual agencies and private organizations, with their own internal data systems, metadata, semantics and so on.

On the other hand, how could Big Data on the urban realm can be useful for architects, urban designers and planners? Drawing on experience from architecture and other industries. There are four ways for designers and planners to use data to improve their work. The first relates directly to the design process, and the others build upon this process to explore other ways that city data can be generated and used to create better places. So far, architects and urban planners have been largely absent from these discussions despite being great users and visualization of data. If the economic, social and environmental benefits of Big Data are to be extended to the spatial disciplines of planning and design, then they need to be connected to the open data and smart city debate (RIBA, 2013).

8. Conclusion

This paper presented the dimension of developing Environmental Sustainability Strategic Planning for cites. The linkage of Big Data and Data Mining to Environmental Sustainability is introduced. Tools and applications Data Mining in Environmental Sustainability of smart cities with examples are illustrated. The Data Mining approach for Environmental

Sustainability Strategic Planning of smart cities with an example of the framework of an Intelligent Environmental Decision Support System (IEDSS) is explained. The example of IEDSS framework presented in this paper can be further developed and extended to support the decision making process on various necessary components included in the Environmental Sustainability Strategic Plan (ESSP), e.g. action items and environmental indicators. For future work it is important to develop the IEDSS to be adaptable to smart cities and users' needs and be user friendly and robust. It is recommended to implement these additional features on an ESSP for a specific city and assess its utility and impact on better supporting the decision making for the environmental sustainability of specific and real city situations.

9. References

1. Ahmed, N. S., "Big Data and Urban Planning in Pakistan: A Case Study of the Urban Unit", Major Paper, *Master in Environmental Studies*, York University, Toronto, Ontario, Canada, (2018).
2. Allam, A., Tegally, H. and Thondoo, M., "Redefining the Use of Big Data in Urban Health for Increased Liveability in Smart Cities", *Smart Cities*, 2, (2019), pp. 259–268.
3. Alzate, C. and Sinn, M., "Improved Electricity Load Forecasting via Kernel Spectral Clustering of Smart Meters", *in IEEE 13th International Conference on Data Mining (ICDM)*, (2013), pp. 943– 948.
4. Al-Zegaier, H., Al-Zu'bi, A. and Barakat, S., "Investigating the Link between Web Data Mining and Strategic Human Resources Planning", *Computer and Information Science*, 4, (3), (2011), pp. 67-75.
5. Cassidy, A., *A Practical Guide to Information Systems Strategic Planning*, 2nd ed. Boca Raton, Florida, Auerbach Publications, (2006).
6. Chowdhury, P., Sutherland, S., Ernst, K., Pawlowski, A., Schmidt, E., Caspersen, J., Zhao, Z. and Bhadur, B., Big Data in Emerging Cities, In: Laurie A Schintler and Zhenhua Chen (eds), *Big Data for Regional Science*, New York, Rutledge, (2018).
7. City Planner, https://www.cityplanner.it/the-online-whatif-gis-based-planning-support-system-tool/ (Accessed 16 November 2019).
8. Costa, C. and Santos, M. Y., "Improving Cities Sustainability through the Use of Data Mining in a Context of Big City Data", *Proceedings of the World Congress on Engineering*, Vol I, London, UK, (2015).
9. Dumbill, E., "Making Sense of Big Data", *Big Data*, 1, (1), (2013).
10. Gama, J., *Knowledge Discovery from Data Streams*, Boca Raton, FL, CRC Press, Taylor & Francis Group, (2010).
11. Giberta, K., Sànchez-Marrèa, M. and Sevilla, B., "Tools for Environmental Data Mining and Intelligent Decision Support", *International Congress on Environmental Modelling and Software, Managing Resources of a Limited Planet*, Sixth Biennial Meeting, Leipzig, Germany, (2012).
12. Hedlund, J., "The Smart City: Using IT to Make Cities More Livable", *A Microsoft Services Enterprise Architecture Paper*, Microsoft Corporation, (2011).
13. Juan, E. et. al., "Methodological Guide: Emerging and Sustainable Cities Initiative", *Inter-American Development Bank*, (2014).
14. Kamrowska-Zaluska, D. and Obracht-Prondzynska, H., "The Use of Big Data in Regenerative Planning", *Sustainability*, 10, (2018), pp. 1-20.
15. Keeso, A., "Big Data and Environmental Sustainability: A Conversation Starter", Working Paper 14-04, *Smith School of Enterprise and the Environment*, University of Oxford, UK, (2014).

16. Laney, D., "3D Data Management: Controlling Data Volume, Velocity, and Variety", *Meta Group Inc.,* (2001). Retrieved from http://blogs.gartner.com/doug-laney/files/2012/01/ad949-3D-Data-Management-Controlling-Data-Volume-Velocity-and-Variety.pdf
17. Mayer-Schönberger, V. and Cukier, K., *Big Data: A Revolution that will Transform how we Live*, London, UK, Work and Think, John Murray, (2013).
18. OECD, *The DAC Guidelines: Strategies for Sustainable Development*, Paris, France, OECD Publications Service, (2001).
19. RIBA: Royal institute of British Architects, *Designing with data: shaping our future cities*, London, RIPA, (2013).
20. Sànchez-Marrè, M., Giberta, K. and Sevilla, B., "Evolving GESCONDA to an Intelligent Decision Support Tool", *International Congress on Environmental Modelling and Software Modelling for Environment's Sake*, Fifth Biennial Meeting, Ottawa, Canada, (2010).
21. Sowe, S. K. and Zettsu, K., "Curating Big Data Made Simple: Perspectives from scientific communities", *Big Data*, 2, (1), (2014), pp. 23-33.
22. Sundaravaradan, N., Patnaik, D. and Ramakrishnan, N., "Discovering Life Cycle Assessment Trees from Impact Factor Databases", *Association for the Advancement of Artificial Intelligence*, (2011).
23. Sutton, P., "A Perspective on environmental sustainability?", *Victorian Commission for Environmental Sustainability*, Victoria, Australia, (2004).
24. Thakuriah, P., N. Tilahun and M. Zellner, "Big Data and Urban Informatics: Innovations and Challenges to Urban Planning and Knowledge Discovery", In *Proc. Of NSF Workshop on Big Data and Urban Informatics*, (2015), pp. 4-32.
25. Thakuriah, P., Tilahun, N. and Zellner, M., *Seeing Cities Through Big Data*, Switzerland, Springer International Publishing, (2017).
26. THWINK (2019). *The Three Pillars of Sustainability*, http://www.thwink.org/sustain/glossary/ThreePillarsOfSustainability.htm (accessed October 19, 2019).
27. ToV: Town of Vail, *Environmental Sustainability Strategic Plan: Code Green – Building a Sustainable Future*, (2009), www.vailgov.com
28. Vilajosana, I., Llosa, J., Martinez, B., Domingo-Prieto, M., Angles, A. and Vilajosana, X., "Bootstrapping smart cities through a self sustainable model based on Big Data flows", *IEEE Commun. Mag.*, 51, (6), (2013), pp. 128–134.
29. Yimin, Z., Wong, M. and Mi, K., "Smart City, Smart Residents: Seoul's 'Smart' Transformation Accelerates Under Mayor Park", *CLC Insights*, (21), (2016).
30. Zhou, H., Wu, X. H. and Li, X. G., "An ANFIS model of electricity price forecasting based on subtractive clustering", in *2011 IEEE Power and Energy Society General Meeting*, (2011), pp. 1–5.