Urban Intelligence: a Modular, Fully Integrated, and Evolving Model for Cities Digital Twinning

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***Abstract* — The Urban Intelligence (UI) paradigm proposes an ecosystem of technologies to improve urban environment, wellbeing, quality of life and smart city systems. It fosters the definition of a digital twin of the city, namely a cyber-physical counterpart of all the city systems and sub-systems. Here we propose a novel approach to UI that extends available frameworks combining advanced multidisciplinary modelling of the city, simulation and learning tools with numerical optimization techniques, each of them specialized for the digital representation of city systems and subsystems, including not only city infrastructures, but also city users and their interactions. UI provides sets of candidate policies in complex scenarios and supports policy makers and stakeholders in designing sustainable and personalized solutions. The main characteristics of the proposed UI architecture are (a) fully multidisciplinary integration of city layers, (b) connection and evolution with the city, (c) integration of participative strategies to include "human-oriented" information, and (d) modularity of application.**

Keywords* — *digital twins, decision making, multidisciplinary analysis and optimization, data lake management, wireless sensing, data/model driven learning and reasoning, know-how integration.

I. Introduction

The concerns for a sustainable future are tightly connected with the spread and continued growth of urban areas, and how these will adequately address fundamental issues such as energy production and resource consumption, the rise of poverty and hunger, healthy life and well-being, biodiversity loss in their borders, economic development: "*any discussion of sustainable development should center on cities and how to capitalize on their positive energy and innate diversity in forging new pathways toward urban sustainability*" [1]. An understanding of the connections and the relevance of the integration of urban planning with new enabling technologies such as modeling and simulations, Internet of Things, Artificial Intelligence for learning and reasoning, is becoming the new paradigm of any new approach to the prediction of future scenarios of urban sustainability and to the generation of long-term policies for the future of sustainable cities. Urban Intelligence (UI) is an eco-system of infrastructures and services that allows the creation of a digital twin (DT) of a complex real/physical system such as a city and its various systems and subsystems (e.g., transportation, energy distribution, water usage, population, education, health, cultural heritage, etc. [1]) including the surroundings in which the city is "immersed". In particular, the UI paradigm leverages crossovers between mobile networking (IoT - Internet of Things), process modelling and artificial intelligence (AI), for learning and reasoning, targeting a city (smart city) where traditional infrastructures are coordinated and integrated using new digital technologies [2]-[3]. A number of DT models have been implemented in India, Southeast Asia, and Europe [4]-[7].

Despite some recent attempts in defining a common/global architecture for UI, most of the current proposals are designed to solve very specific problems, while they could not provide effective generalizations [8]. We propose instead a unified

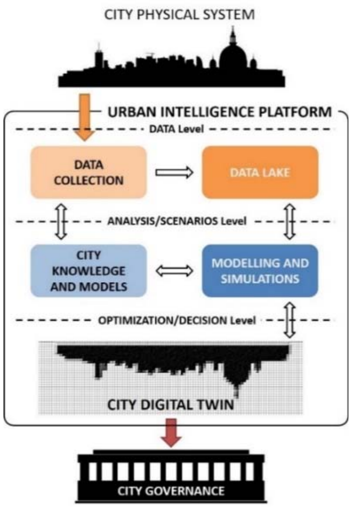


Fig. 1. Proposed UI architecture.

approach where the digital model of the city is organized into layers that cooperate and reconfigure to solve assigned problems and make high level decisions through an integrated and coordinated multidisciplinary approach. In addition, the proposed UI architecture allows for the virtual representation of all the city systems and subsystems, including not only the city infrastructure, but also city users and their interactions. UI methodology will promote an evolution of Smart City approaches, developing new directions: (1) integrated and intelligent systems for the government of the city, using multiple data (from sensors to Citizen involvement) allowing for a quasi-real time integration of heterogeneous data controlled by multidisciplinary optimization approaches; (2) a flexible and adaptive digital model that learns from and evolve with the real city; (3) a predictive model capable of anticipating future scenarios.

The proposed UI architecture differs from the state of the art in the following four key features:

a) Fully integrated: the present UI extends existing frameworks (e.g., [8]-[9]) to enable complex interdependent analyses of all layers, systems and subsystems. These are considered as a part of a fully integrated model of the city, whose interactions are handled and solved via multidisciplinary analysis (MAO) schemes [10]. UI integrates data- and model-driven management systems, that use both sensor data from different sources (historical and real time series) and predicted data obtained from layers' modelling and simulations.

b) Connected and evolving: the present UI is natively built to comply with current IoT installations and 5G technology [11] and support highly dynamic and complex scenarios. Sensors are connected through a distributed low-latency 5G network and are used to monitor the city status in real-time as well as to follow its evolution. Real-time data analytics is obtained by combining advanced AI systems and edge-cloud computing [12] with model-based numerical optimization of multiple city layers through multidisciplinary optimization MDO [10]. This allows the digital system to simulate fine-grained optimal reaction to an external event by automatically reprogramming itself and delivering multiple policies.

c) Going human: the present UI is not limited to smart cities infrastructures [13] but also engage citizens and city stakeholders in participatory processes, to integrate participatory models in the city DT. This allows to obtain a more flexible "human-oriented" DT model incorporating city users' needs and their evolution.

d) Modular: the present UI is an implicit (*three dimensional*) modular scheme: it can be applied to: (i) a limited part of the city (space dimension), (ii) a limited number of sub-layers (layer dimension), and (iii) a limited number of interactions among the layers (interaction dimension). Each of these three dimensions can be exploited according to the complexity of the task, availability of data, difficulty in developing simulators, and DT models, etc. This allows for initial development of the DT at a reasonable cost, with successive extensions and deepening of the analysis as needed.

II. The Proposed Urban Intelligence Architecture

As summarized in the diagram of Fig. 1, the proposed UI architecture is based on a platform organized into three levels, namely: i) the *data level,* handling the data collection, preprocessing, distribution, and storage; ii) the *analysis level* that is in charge of process modelling of the city sub-systems and analytics; and iii) the optimization level for delivering high level decisions through the coordination of all the scenario-dependent models and analysis.

The UI platform consisted of five interconnected and integrated modules, namely 'city knowledge and models', 'data collection', 'data lake', 'modelling and simulations', and 'city DT' that use key enabling technologies, such as IoT networks, data science and modelling, high performance computing and advanced numerical optimization. The following sections highlight the characteristics of the five components of the UI platform.

A. City Knowledge and Models

The proposed UI paradigm is characterized by two key features: on the one side, the DT of the city, whose status is continuously updated thanks to sensor networks, and on the other side, a set of numerical methods able to simulate and/or optimize processes related to or taking place into the city itself. In order to build this complex system, the knowledge and data about the physical city itself should be properly modelled in an abstract and structured manner in order to set-up the "backbone" of the DT.

We envisage a digital city model structured according to the prominent sub-systems relevant for urban analysis, coupling state-of-the-art technologies for modelling in 3D the morphology and physical structures (built or natural) with knowledge technologies for abstracting and modelling those urban analysis processes that we want to elaborate in the UI platform, exploiting the power of computer-assisted simulation and optimization strategies.

Digital data about cities are nowadays ubiquitous, coming from laser or photogrammetric acquisition methods, and methods for 3D reconstructions of urban scenes have been studied since decades by now [14]. At the same time, CityGML [15] provides a perfect background for the abstract representation of knowledge items related to most urban analysis processes.

The approach proposed by our UI paradigm builds on a tight coupling of knowledge and digital 3D city representations, exploiting the potential of shape-based and part-based annotation of 3D models [16]. Formalized knowledge, or semantics, will be used to organize and structure 3D representations of the cities: the digitization of a city may easily produce huge amounts of digital data whose handling needs proper design. Organizing 3D data according to semantics provides a natural, yet effective, data management strategy.

We want to underline indeed that, while challenges related to the visualization of big city data have been studied and solutions exists for their rendering using level of detail techniques, the UI paradigm pushes the usage of 3D data beyond visualization: simulations and numerical methods may indeed require knowledge about the geometries of the entities on which they are acting and use them as boundary conditions, for instances. Also, we envisage that a set of basic analysis tools might be developed to extract automatically from the 3D model of the city to measure potentially everything which is nowadays measured physically.

According to the proposed UI paradigm, the city model design and development takes place in the start-up phase of the platform construction: capitalizing on data about the city physical structure (i.e., cartography, laser scans), data/information relevant to structure the city layers of interest will be collected and indexed properly to make them accessible by services developed by the UI platform. In parallel, metrics for evaluating the status of each relevant city sub-system will be defined together with computational methods to evaluate them on the city DT.

B. Data Collection

The data collection module is designed to acquire and process sensor data and signals useful for maximizing urban wellness, accessibility, inclusiveness, safety, mobility and the design of 'smart' (i.e., sustainable) solutions having maximum efficiency and low impact on the city. Data and signals come from three different sources, namely from (1) sensors, (2) participatory tools, and (3) actuators.

1) The network of sensors. The wireless network is in charge of the distribution of data and signals obtained from different sensors, typically densely deployed. In line with the 5G new radio (NR) framework [17], sensors should adopt the massive machine type connectivity (mMTC) paradigm [18] (NB-IoT or eMTC specifications). Alternatively, SigFoX and LoRa (Long Range) radio interfaces can be used over unlicensed bands. The network of sensors is designed to collect data and signals (raw or pre-processed for noise/outliers removal) coming from three main and interconnected components, namely from (a) the environment and natural resources, (b) the users, and (c) the infrastructure, as described below. These three components contribute to characterize the city and its DT model.

a) Environment and natural resources. Air quality, temperature, environmental noise and exposure to electromagnetic fields in the broadband spectrum (ranging from electric power lines [19] to telecommunication facilities or other sources of radiation [20], including 5G networks and sensors) are the key variables that are acquired. A number of additional variables related to the environment that indirectly contribute to the perception of the citizen's well-being are measured as well. Hydrometeorological conditions, water quality, use of natural resources, and monitoring of living plants' health are examples of such variables that will be acquired both by 24h measurements with sensors and by the analysis of time series.

b) Users. Parallel to the aforementioned environmental variables, the network of sensors also measures data and variables directly from the 'users' of the city, i.e., by those people (citizens and tourists) who interact with the city and its infrastructure using different modalities. Data from users are analyzed an processed for the development of optimized and customized 'urban wellness' strategies that are fitted on the specific needs and characteristics of the city and its users to improve health and reduce risks. Data from the users are measured and monitored in a minimally invasive manner both with passive sensors that do not require an active participation of the subject and with technologies that allow interaction with the user to detect preferences and needs in real time. Examples of the technologies for passive sensors include wearable sensors for personal monitoring of activity-related variables and physiological signals (e.g., heart rate, respiration rate, subject dehydration) and remote sensing for the estimation of people mobility and flows by exploiting a series of information generated by the telecommunications networks during their operation. As to interactive technologies, information from for example online social networks are used to provide the DT model with a urban wellness index of the geographical area of the city. Overall, these variables are used to develop solutions not only to promote the users' and the city wellness, but also to improve inclusiveness of people with disabilities, safety and better knowledge of the artistic/cultural heritage of the city.

c) Infrastructure. As far as the infrastructure of the city, there are several variables of interest, including those related to vehicular connectivity achieved through new radio connectivity technologies, monitoring of structures of artistic/cultural interest, and monitoring of service infrastructures.

2) The participatory tools. In addition to the network of sensors, participatory tools, such as apps, questionnaires, etc., are implemented to provide data from non-specialized figures (such as citizens) and thus promote participation and action in decision-making processes. Data acquired with participatory tools are of various types including text, images, audio files.

3) The actuators. Finally, the DT model also uses the data from a network of intelligent actuators that is developed to act on the "city system" according to the solutions designed by the other modules of the proposed UI platform.

C. Data Lake and ICT platform

The general aim is to develop an ICT platform to store, manage, access, and analyze the amount of data acquired from the sensors, participatory apps, and from all other data sources required by the city model developed in Section II.A.

Data lake is a concept referred to a method to organize a large amount of data (such as, big data, which can be in native format, formatted, or can be the output of processes) for documentation, visualization, data analytics, and knowledge acquisition. The data lake consists of a static component - the data (including all the data sources needed to the city model developed in Section II.A) - and a dynamic one which provides the functionalities to manage and exploit these data.

The proposed paradigm of the urban DT becomes operational through an ICT platform which helps the management of all the sub-systems of the urban organism, which are modeled in the city model by providing the following services to citizens, operators, and apps:

- hosting the digital version of the USRM, i.e. the urban DT;
- collecting, storing, managing, and providing to all the platform components, citizens and operators with credentials the data acquired by sensors, IoT, participatory apps, DBMS, other data sources;
- monitoring the behavior of each layer composing the DT;
- recording in the city model and in the DT the modifications occurred in the real system;
- allowing access and interaction with each layer (each one characterized by a simulation module) of the DT, independently from the protocols used for user interaction, integration of third-party applications, inclusion of simulation modules;
- monitoring the status of the inter-connections among simulation models;
- the platform kernel manages information on simulation modules, their characteristics and metadata; integrates the simulation modules by means of suited API;
- a fundamental aspect for the simulation modules could be considered twinning a specific sub-system of the physical system with the physical system represented by the city model; therefore, the ICT platform should offer a dedicated component with all needed communication functionalities.

D. Modelling and Simulations

A relevant issue in our use of the DT is the development of multiple ways to exploit sense-reason-act loops using different technologies to simulate the subsystems of the city. This approach allows to adopt the most appropriate technology to model the specific features of the city and implement control policies for heterogeneous physical phenomena taking advantage of the peculiarity of each simulation technology. The intuitive idea is that for example, some of the phenomena are described by large amount of data and hence can be modeled with analytic tools based on machine learning; in other cases more "classical" models that implement well-defined mathematical structures better match the case; in other cases the phenomena escape from a clean formal account and "old fashioned" handcrafted AI models based on knowledge representation and reasoning may allow to capture the structure of the problem and addressing its solution (e.g., with problems that interact directly with humans in which a shared representation plays a role). A key aspect in our UI paradigm is the idea that the "one approach fits all" is not viable for complex and interconnected phenomena like those of big cities, rather it is more appropriate put together different approaches taking advantage of the specificity of each of them. A peculiarity in our work is the attention to control complex phenomena where dynamicity plays a key role, hence a common feature is the approach based on reasoning and acting developing a number of special purpose controllers (while the multi-disciplinary optimization sketched in Section II.E has the role of reconciling the different approaches in a coordinated optimization able to cope with heterogeneity).

Just for extending a bit the analysis, we just refer to one aspect connected to the high availability of data coming from heterogeneous sources. This represent a precious and valuable information that can used to perform complex operations and services. The desiderata are represented by an efficient processing of huge sets of data coming from the "real-world" and a development of artificial systems that autonomously and proactively make decisions. These desiderata often clash with the reality of problems. One important consideration is that when technology and, for example, Artificial Intelligence are capable of autonomously make decisions that impact on the daily life of common people, it is important for humans to understand the decisions that these algorithms make and directly (or indirectly) control these decisions. As a consequence, explainability is a well-known problem of new data driven learning-based technologies because it is not always easy or possible to explain in human terms the decisions made by the algorithms. Indeed, in the proposed UI paradigm we are working on a rather orthogonal direction that can be summarized as follows: first clearly identify a smart correspondence among features of the problem and a more suited approach to their solution, then develop an infrastructure for both interoperability of the problem solving approaches and their integration on the same scenario. See the next section for our current direction for such an integration.

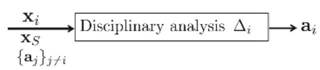
Indeed, it is also worth saying that this is just one possible direction. It is to note that to solve complex societal problems it is relevant to offer End-to-End solutions for both decision makers and citizens. The ability to select the right tool that best fits with the structure of the current "active" problem and the development of methods and techniques to integrate the approaches are important factors to be considered.

E. City Digital Twin and Decision Making via Multidisciplinary Analysis and Optimization

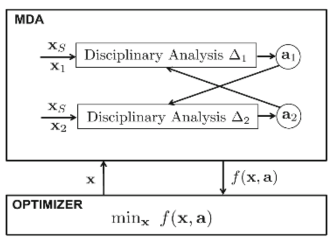
Modeling and simulation tools in Section II.D provide data-driven, physics-based, and assimilated models for each disciplinary domain. Their integration into (from low to high level) sub-system, layer, and city models is achieved through multidisciplinary analysis (MDA), which manages and solves the interaction among different disciplines, providing the desired multidisciplinary consistency [10]. The decision-making process follows multidisciplinary optimization (MDO) architectures and methods [10], providing with both open- and closed-loop solutions for policy makers.

In the context of the current proposal, MDA provides the desired DT of the city through integration of all modules (Sections II.A-D). The city MDA incorporates the main characteristics associated to the DT of a real physical system [21]: *connectivity, data fusion and assimilation, adaptivity, and modularity*. Connectivity is achieved through integration of sensor data and IoT (Sections II.B and II.C). Data fusion of multiple data sources and assimilation of theoretical and physics-based models with observations/data-driven models is the core of the twinning process and is achieved by integration of models from Sections II.A and II.D. Adaptivity is obtained by continued learning from sensor data, making the DT growing *with and as* the physical city. Finally, modularity is an intrinsic characteristic of MDA, providing the opportunity to add/extend/enhance disciplinary models and components.

Within the current UI, the DT/MDA is interrogated to support policy makers via MDO formulations of the decision-making problem. The ambition is to achieve families of multidisciplinary multi/many-objective optimization solutions, spanning mixed-integer optimization domains affected by both epistemic and aleatory uncertainties associated to the variability of input parameters, accuracy of models and simulations, prediction and forecasting. Due to the complexity of the problem, the presence of local optima and/or local non-dominated solution sets cannot be excluded. Therefore, the development/use of global MDO methods is highly desirable.



At the discipline/sub-system level, the input/output relation (provided by either data-driven, physics-based, or assimilated models) is represented as shown in the figure above, where $\mathbf{x}_i$ collects decisions/policies affecting the i-th discipline/sub-system and $\mathbf{x}_S$ represents decisions/policies shared by all sub-systems/layers, respectively; $\mathbf{a}_k$ are output parameters/indicators of the k-th discipline/sub-system used as input by other disciplines/sub-systems. The integration of disciplinary analyses into MDA ad its extension to MDO is schematized in the side figure (with a two-discipline example), where an optimizer interrogates the MDA to provide candidate optimal solutions for policy makers. The algorithmic and numerical complexity stemming from the interconnection of multiple city layers and their multidisciplinary optimization imposes the development of cutting edge global MDO methods [22], possibly including reliability-based robust formulations.



III. Conclusions

The paper proposed a novel architecture and approach to UI consisting of a DT model of the city organized into layers that cooperate and reconfigure to solve assigned problems. The UI architecture is designed to make high level decisions through a coordinated multidisciplinary approach, leveraging (a) fully multidisciplinary integration of city layers, (b) connection and evolution with the city, (c) integration of participative strategies to include "human-oriented" information, and (d) modularity of application.

Finally, the proposed methodology for urban planning could lead to some significant results onto three intervention levels: (1) strategic level of planning and intervention on fundamental city infrastructures, mobility system, energy distribution, etc., (2) operational level of urban planning, in connection with services management, local mobility planning, building design and performance, site and settlement planning; and (3) emergency level for integrating resiliency and sustainability into emergency preparedness.

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