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# Smart city model based on systems theory

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ABSTRACT

While there are several partial solutions to model some aspects of cities (e.g. transportation or energy), there is no framework allowing modelling of a complex system such as a city. This paper aims on providing a solution that can be used by practitioners to model impact of different scenarios and smart city projects encapsulating different subsystems, such as transportation, energetics or, for example, eGovernment. The term “smart cities” is classified into Systems Theory, particularly focusing on Cyber-Physical Systems. This classification is further elaborated to define a new term, so-called Smart City Agent (SCA). The SCA is considered as the main building block for modelling smart cities. The approach within this paper however stresses the interconnection of different systems within a city. Its’ strength is in better exchange of data and among heterogeneous agents. This information management approach is the missing key in the growing market of partial smart city solutions as it will allow simulation of solutions in complex systems such as a city. The suitability of usefulness of the proposed approach is demonstrated on a use case dealing with charging of electrical vehicles. The results show that the approach is suitable for modelling of dynamic behaviour.

## 1. Introduction

The area of smart cities is currently undergoing a quick development and many different solutions are emerging on the markets. It is estimated that by 2030 more than 100 billion dollars will be invested in smart city applications (Visvizi & Lytras, 2018). In the paper (Lom & Pribyl, 2017), a modelling approach of smart cities called SMArt City Evaluation Framework (SMACEF) was introduced. SMACEF is the modular framework that allows modelling of the current state of a system as well as its future states, and based on defined scenarios and key performance indicators (KPIs) can be benchmarked which the proposed solution is the best one. In other words, the goal of the framework is to evaluate if the proposed solutions are beneficial and useful for cities or not.

The modelling approach is based on the Multi-Agent Systems (MAS). Every object is represented by an intelligent agent. The practical implementation of SMACEF was published in the paper (Pribyl, Lom, & Přibyl, 2017). Based on SMACEF, a new type of an intelligent agent – Smart City Agent (SCA) is introduced and described as a building block for modelling smart cities in this paper. The area of smart city modelling is classified to the theories of Systems Theory and Cyber-Physical Systems, and both can be modelled by Multi-Agent Systems.

The Smart City Agent is a modified version of an intelligent agent. It is more suitable for benchmarking and evaluating purposes in smart cities. The practical example of an implementation of Smart City Agents using SMACEF is demonstrated. Cities are dynamic and nonlinear systems and for this reason the models have to be dynamically simulated with different scenarios, and the results of these simulations should be benchmarked.

The proposed solution can be directly used by practitioners to model dynamic behaviour of interacting subsystems. The literature review shown that at the present, there is no alternative solution to this task and city representatives are depending on the providers of partial solutions.

In the Sections 2,3 and 4, a city is classified into the Systems Theory and Cyber-Physical Systems. In the Sections 5 and 6, modelling of smart cities is fitted into Multi-Agent Systems. The Section 7 deals with the definition of Smart City Agent followed by the use case, evaluation of the results and discussion.

## 2. Background

A system according to (Rousseau, 2015) is: *“a set of interacting or interdependent component parts forming a complex whole. Every system is delineated by its spatial and temporal boundaries, surrounded and influenced by its environment, described by its structure and purpose and*

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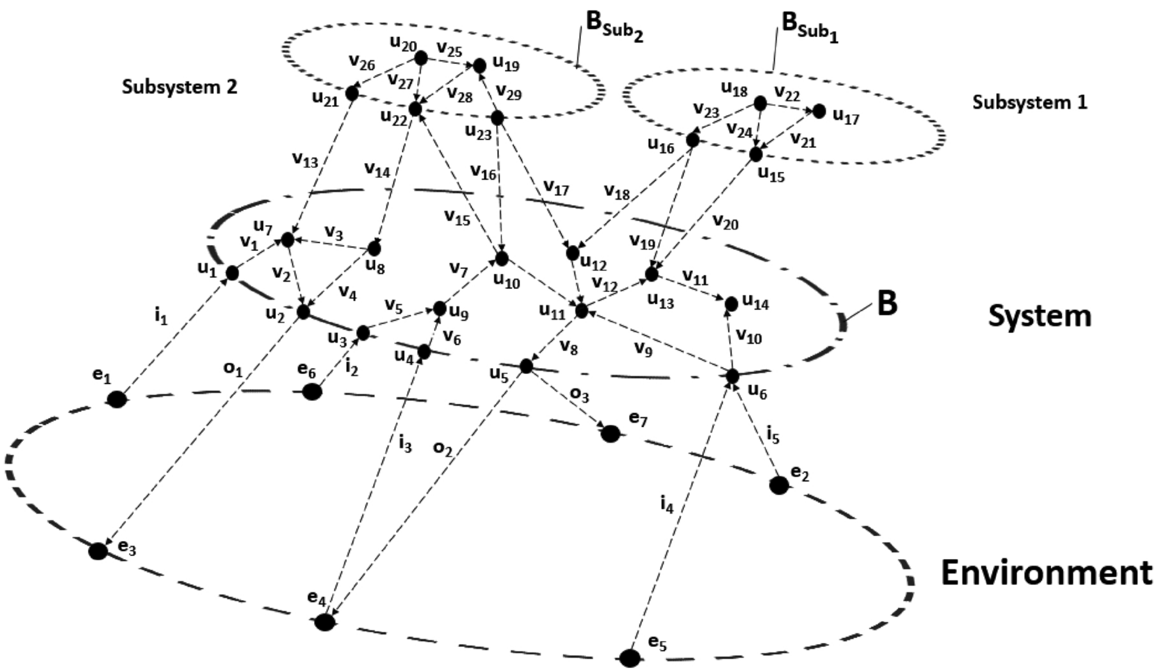


**Fig. 1.** The example of a system.

*expressed in its functioning."* A system can be divided into subsystems. A subsystem is a separable and identifiable part (component, element) of a system. An example of a system according to the Systems Theory is depicted in Fig. 1.

The system consists of subsystems and is surrounded by its environment. The system is defined by its structure $S = (U, V)$ using a set of internal objects (universum of system) U = ($u_1$,…,$u_{23}$) and a set of internal relations $V = (v_1,…,v_{29})$. The example of an object, $u_i$, can be a parking sensor or a cloud and an example of internal relations, $v_j$, can be a communication between the parking sensor and the cloud. The system in this example has its boundaries defined by $B = (u_1, u_2, u_3, u_4, u_5, u_6)$. The boundaries can be seen as interfaces among systems, subsystems and environment. Accordingly, the subsystems have their boundaries defined by $B_{sub1} = (u_{15}, u_{16})$ and $B_{sub2} = (u_{21}, u_{22}, u_{23})$. The system has also its input $I = (i_1, i_2, i_3, i_4, i_5)$ and output relations $O = (o_1, o_2, o_3)$ as well as input $U_i = (u_1, u_3, u_4, u_6)$ and output objects $U_o = (u_2, u_5)$. The subsystem 1 has only output relations $O_{sub1} = (v_{18}, v_{19}, v_{20})$ and output objects $Uo_{sub1} = (u_{15}, u_{16})$. The subsystem 2 has input $I_{sub2} = (v_{15})$ and output relations $O_{sub2} = (v_{13}, v_{14}, v_{16}, v_{17})$ as well as the input $Ui_{sub2} = (u_{22})$ and output relations $Uo_{sub2} = (u_{21}, u_{22}, u_{23})$. The environment is defined by a set of external objects $E = (e_1, e_2, e_3, e_4, e_5, e_6)$.

A city according to (James, Holden, & Lewin, 2013) is: *"a large and permanent human settlement and cities generally consist of complex subsystems for example for sanitation, utilities, land usage, housing, or transportation. The concentration of development greatly facilitates interaction among people and businesses, sometimes benefiting both parties in the process, but it also presents challenges to managing urban growth."*

According to Systems Theory and the example in Fig. 1, a city can be defined as an environment which consists of multiple systems that can be divided into subsystems. The examples of systems within a city can be represented by energy or transport systems. For example, energy network or power plants are subsystems of the energy system, and vehicles or infrastructure are subsystems of the transport system. The example with the particular systems is shown in Fig. 2.

## 3. Cities versus smart cities

What is a difference between the terms "traditional cities" and "smart cities" in this paper? In the traditional cities, (sub)systems are commonly able to interact only with their environment. It means that systems are mostly stand-alone and not interoperable with other systems. On the other hand, one of the main goals of smart cities is to interconnect different systems and subsystems among themselves to increase the quality of life, energy savings or to reduce emissions. The main difference between the traditional and smart cities according to the Systems Theory is demonstrated in Fig. 2 and the Fig. 3.

In Fig. 2, the (sub)systems of the transport system do not interact with other (sub)systems and only interact with the environment. In the Fig. 3, the individual (sub)systems of the transport system are interconnected with the (sub)systems of the energy system. In smart cities, such interconnections among (sub)systems can represent exchange of information or energy (resources). The particular example can be that an electric car is able to communicate directly with the energy network and reserve a performance for itself, or the infrastructure can communicate directly with power plants to optimize energy supplies based on the demand from vehicles at the infrastructure. Within a city, many other systems exist. Energy and transport systems has been selected to show a particular example.

## 4. Smart cities as cyber-physical systems

Based on the previous sections, cities can be generally considered to be seen as an environment according to the Systems Theory. Nevertheless, this theory is very broad and the entire Systems Theory can be divided to several specific subsets. One of these is called Cyber-Physical Systems (CPS) and we demonstrate that cities can be considered to be CPS. Several papers related to this topic has been already published (Hashem et al., 2016a). In simply terms, CPS means that the physical and virtual (software) world are interconnected (Lee, Bagheri, & Kao, 2015).

This perfectly fits to the aims of smart cities and allows us to interconnect particular systems (e.g. energy, transport, buildings). The physical part of the smart city is generally based on a network of sensors and actuators embedded through-out the urban terrain, interacting with wireless devices (e.g. tablets, smartphones) and having an Internet-based backbone with cloud service (virtual part of CPS). The data collected and flowing through such CPS may involve traffic conditions, the occupancy of parking spaces, air/water quality information,

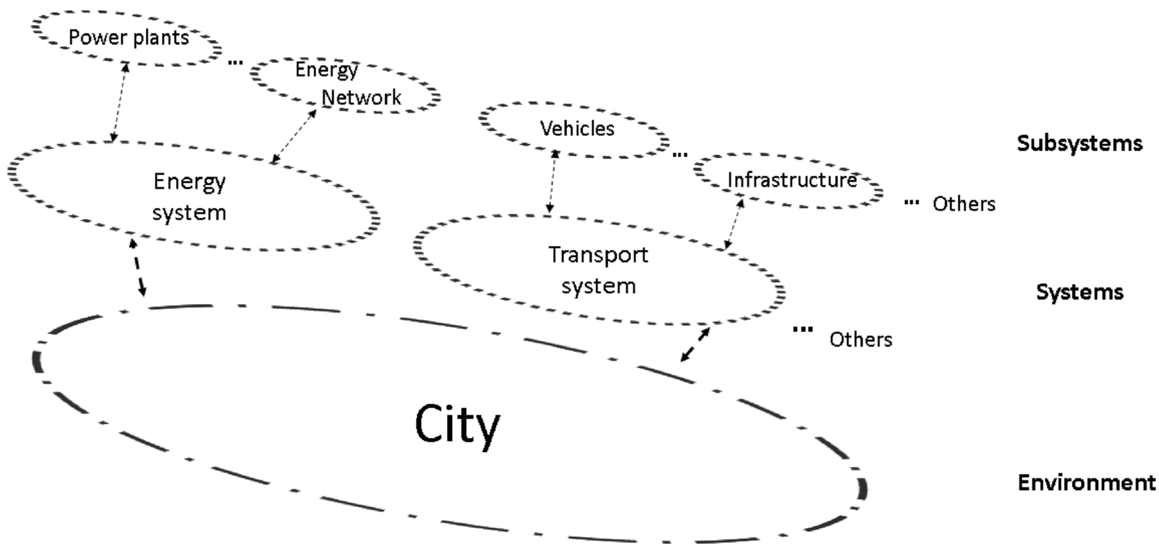


**Fig. 2.** The example of a traditional city fitted to the Systems Theory.

the structural health of roads or buildings, and the location and status of city resources including transportation vehicles, police officers or healthcare facilities (Hashem et al., 2016a).

Smart cities are mainly about collecting and disseminating data. As shown in the Fig. 4, to view the smart city (in terms of CPS) as a closed-loop system is extremely important and, in some cases, critical. Simply collecting and disseminating data to user groups can in fact be more harmful than helpful (Ismagilova, Hughes, Dwivedi, & Raman, 2019). As an example, today's “smart parking” technology essentially informs drivers about available parking spaces. As a result, it is often the case that multiple drivers converge to where a few spaces are available, thus creating additional traffic congestion from drivers attracted to the area who cannot find a space (Geng & Cassandras, 2013).

The smart city can be classified as CPS where computing elements coordinate and communicate with sensors, that monitor physical indicators, and actuators, that modify the physical environment, where they operate. CPS often seeks to control the environment in some way. CPS uses sensors to connect all distributed intelligence in the environment to gain a deeper knowledge of the environment which enables a more accurate control. In a physical context, actuators act and modify the environment where users live. In a virtual context, CPS is used to collect data from the virtual activities of users such as their involvement in social networks or e-commerce sites. Then, CPS reacts in some way to this data to predict actions or needs of users as a whole (Lee et al., 2015).

CPS can be defined in the same way as a traditional system according to the Systems Theory. The main difference is demonstrated in the Fig. 5. The physical and virtual world are interconnected in CPS. The boundary between systems is called an interface. In case of CPS, communication interfaces are important. This concept is the key to the smart cities, because these interfaces are used for interactions and sharing information. Interfaces allow to create a modular system that can be easily changed or extended. As depicted in the Fig. 5, an energy system has two interfaces; the first one for energy supplying to other systems such as vehicles or buildings (physical part); and the second interface, which is used for communication with a cloud (cyber or virtual part).

## 5. Modelling of smart cities

There are two main approaches to modelling cities – analytical and heuristic. From the analytical point of view, the concept of systems is shown in the Fig. 6, where $i(t)$ is a vector of input variables, $o(t)$ is the vector of output variables and $v(t)$ is a vector of state variables. The

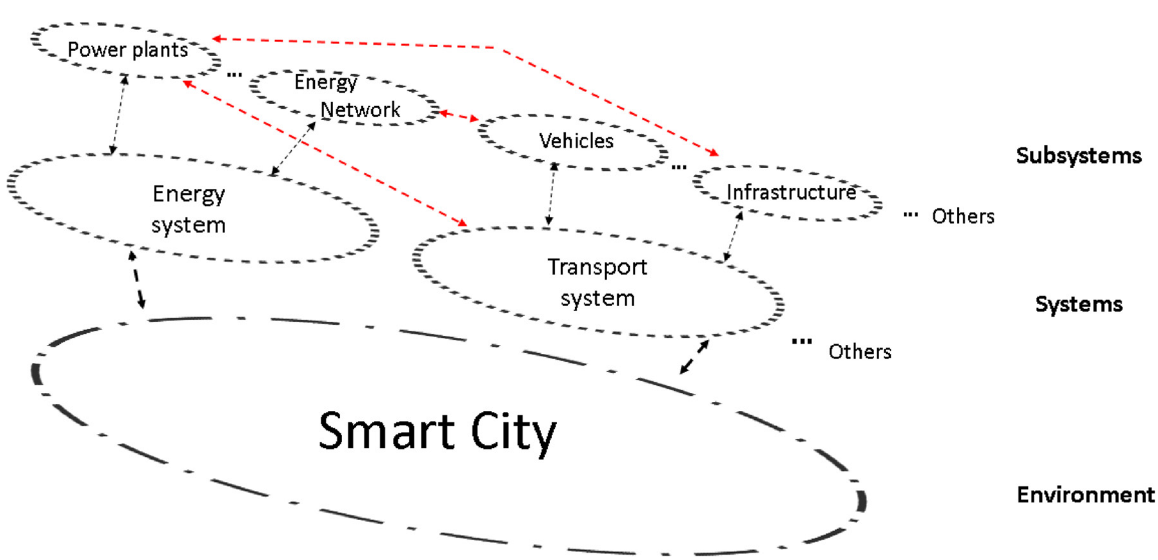


**Fig. 3.** The example of a smart city fitted to the Systems Theory.

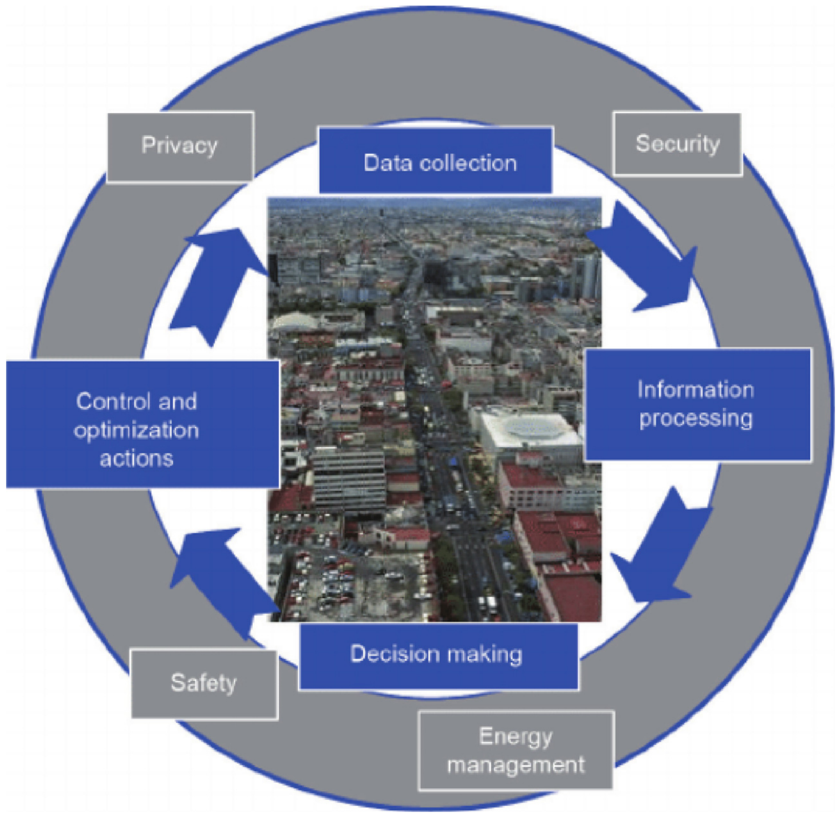


**Fig. 4.** Cyber-physical system as a smart city (Hashem et al., 2016a).

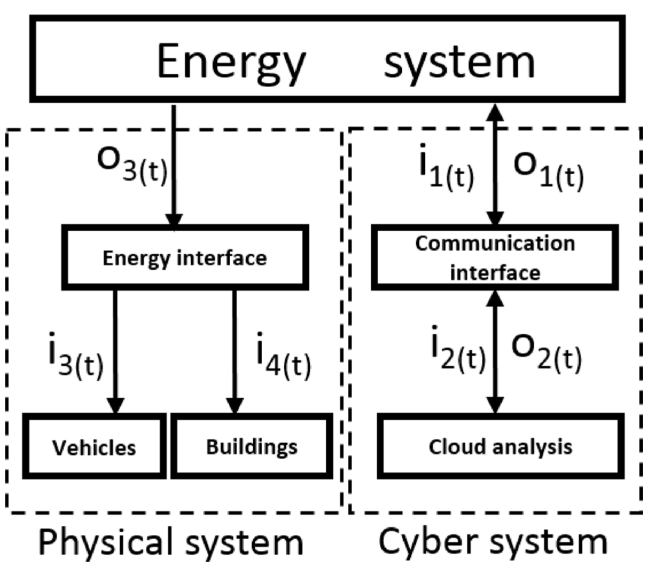


**Fig. 5.** The example of CPS as Energy system.

systems interact among themselves via inputs (*i(t)* in the Fig. 6) and outputs (*o(t)* in the Fig. 6). In case of a transport infrastructure, transport demand is an example of the input, and traffic intensity is an example of the output. The same approach can be applied to the interaction of subsystems.

The term interconnection (or interaction) of (sub)systems means information, energy or control relations among (sub)systems. Cities are stochastic, dynamic and nonlinear systems. One of the main reason is that human behaviour cannot be exactly predicted (Nomura, Kanda, & Suzuki, 2008). The internal description of a dynamic nonlinear stochastic system is defined by the equations 1.1 and 1.2 below (Markus, Majchrzak, & Gasser, 2002):

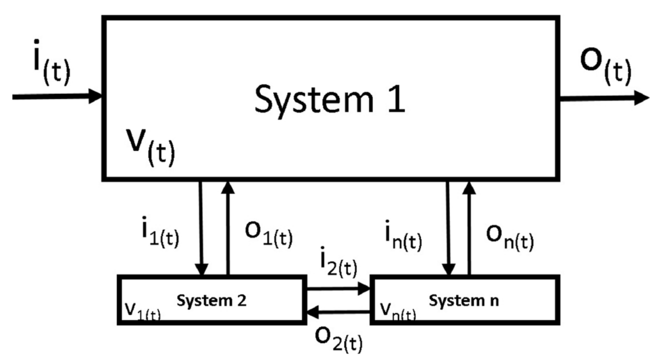


**Fig. 6.** The basic concept of the smart city as a system.

$$v(t) = f(v(t),i(t),t) + x(t) \tag{1.1}$$

$$o(t) = g(v(t),i(t),t) + y(t) \tag{1.2}$$

where *x(t)* is the noise of the process and *y(t)* is the noise of the measurement. The interconnection of (sub)systems is a complex area, because the goals of (sub)systems are different and often contradictory. It is very important to find a balance among the goals of (sub)systems and ensure that the entire system converges to a desired goal(s). Several papers demonstrating how to do this have been published (Alam, 2015). The analytical model of cities is very complex as seen from the equations above. To use an analytical model including the state of a system, all input variables and the uncertainty in measurements for complex systems such as smart cities is very challenging if not impossible (Rzevski & Skobelev, 2014). The authors Rzevski and Skobel also provide a definition of complexity, as *"a property of an open system that consists of a large number of diverse, partially autonomous, richly interconnected components, often called qgents, has no centralised control,* *and whose behaviour emerges from the intricate interaction of agents and is therefore uncertain without being random "*.

For this reason, so called heuristic models are often use as an alternative when dealing with complex systems. Heuristic algorithms or models find approximate (close to optimal) solutions but within an acceptable (finite) time horizon. They typically work based on an informed estimation, intuition, experience or just common sense (Pearl, 1983). As discussed in the previous section, smart cities can be generally classified to Systems Theory and specifically as CPS. These theories can be modelled by various tools like system dynamics or Multi-Agent Systems (MAS). MAS is very useful for modelling smart cities and every object can be modelled as an intelligent agent. In our previous papers (Lom & Pribyl, 2017; Pribyl et al., 2017), the SMACEF was introduced and based on MAS that are one of a well-known heuristic approach with many references Weiss (2013).

## 6. Smart cities and multi-agent systems

The MAS is a tool used for modelling and simulating of various models. This tool is often used in similar areas and provides good results (Lin, Sedigh, & Miller, 2010; Sanislav & Miclea, 2012). Generally, an intelligent agent can be imagined as a software model of a physical object (building, car, street lamp, etc.) that based on its perception P = ($p_0$,…,$p_n$) (sensing) of environment E = ($e_0$,…,$e_n$), where is located, makes a certain decision and based on it performed an action A = ($a_1$, …,$a_n$) affecting the environment. The agent has also its internal states S = ($s_1$,…,$s_n$) (Weiss, 2013). The Fig. 7 shows the basic concept of the agent in its environment.

In the Fig. 1, every object (internal *u* as well as external *e*) can be viewed as an agent and modeled by MAS. It means that every system consists of a set of agents. These agents can interact directly with each other via input/output interfaces. The other view can be via an ontology agent that collects knowledges about a particular (sub)system and can share them with others if necessary (Wang, Shen, & Hao, 2006). The ontology agent can be seen as boundaries of (sub)systems.

The basic example of CPS modeled by MAS is shown in the Fig. 8. Four agents are defined in this example – a human, a cell phone, a cloud and an autonomous vehicle. Every agent has a set of perceptions P, a set of actions A and a set of internal states S. The environment is defined by a set of environment states E. The analogy with the definition of a system defined above can be seen.

Imagine a scenario where a human wants to communicate with an autonomous vehicle via a cloud. The human performs an action $a_1$ that is perceived by the cell phone as $p_1$. The cell phone sends a request $a_2$ to the cloud $p_2$ that resends the request $a_3$ to the autonomous vehicle $p_3$. The autonomous vehicle confirms the call and sends a response $a_4$ back to the cloud $p_4$. This response $a_5$ is sent back to the cell phone $p_5$ and finally the message $a_6$ is read by the human $p_6$. In this example, the basic principle of communication and interacting of the different components within CPS as modeled by MAS is demonstrated.

## 7. Smart city agent

In this section, the definition of an intelligent agent is modified in order to better meet the modelling requirements of smart cities related to simulation and modularity. This newly defined agent based on the

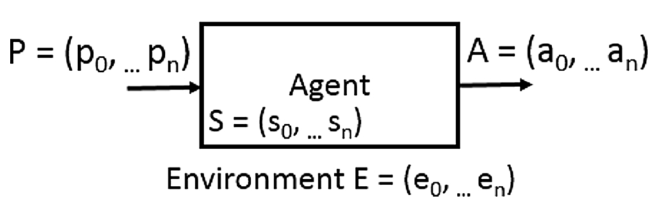


**Fig. 7.** An agent in its environment (Weiss, 2013).

theory of an intelligent agent is called a Smart City Agent (SCA). Every object in a smart city can be modelled as SCA and is characterized by a set of input interfaces (inputs / perception), output interfaces (outputs / actions), parameters, internal states, actions, input/output connections and environmental states (Pribyl et al., 2017). The basic concept of SCA as defined in this paper is depicted in the Fig. 9.

A set of inputs $I = (i_1,…,i_n)$ provides an interface for interacting with an environment defined as a set of environment states $E = (e_1, …,e_n)$ or with another agents defined as a set of input connections $Ci = (c_{i1},…,c_{in})$. This is the first difference compared to the theory of classical MAS. The classical MAS expects to interact directly with the environment. It does not always need to be true in smart cities. Imagine, for example, a motion control of a lamp. A motion sensor observes a change in the environment state and this information is sent via the output interface through the connection to the input interface of the lamp. Based on this information, the lamp changes the light intensity. A set of parameters $P = (p_1,…,p_n)$ provides an "internal tuning" variables that can be used for parameterizing, e.g. an individual device performance. We can use a parameter named performance to determine its performance (e.g. 100 W). This is the second difference compared to the classical MAS theory, as there are no internal variables. A set of internal states $S = (s_1,…,s_n)$ represents the current states of an agent, which can be changed based on inputs. In case of the lamp, the internal state can be a level of light intensity by which the lamp is currently lighting. This internal state can be modified according to the motion. A set of agent's actions is represented by $A = (a_1,…,a_n)$. Actions are generated based on changes of internal states. If the internal lamp`s state (light intensity) is changed, the lamp increases or decreases its performance and appropriate actions are performed. These actions are linked to a set of outputs $O = (o_1,…,o_n)$ that again provides an interface for interacting with the environment defined as a set of environment states $E = (e_1, …,e_n)$ or with another agents defined as a set of output connections $C_o = (c_{o1},…,c_{on})$. This theory is transformed into the SMArt City Evaluation Framework (SMACEF) that has been introduced in the paper including of a practical example (Lom & Pribyl, 2017).

## 8. Use case: modeling of charging of electric vehicles

To show how to design some project, let us focus on modeling of the charging of Electric Vehicles, where two Smart City Agents are defined - Electric Vehicle Agent (*EVA*) and Charging Station Agent (*CSA*) (Csonka & Csiszár, 2017). More detailed explanation of this use case was presented in (Lom & Pribyl, 2019). Here, the authors describe only the part relevant for demonstrating the practical application of Smart City Agents. The internal diagram of EVA is shown in Fig. 10. The *EVA* has two input interfaces – $EV_{com}$ and $EV_{energy}$. $EV_{com}$ represents the interface which is used for receiving messages from a charging station(s) to the vehicle. The interface $EV_{energy}$ is used for charging the vehicle by electricity from a charging station. The subsequent input connections are defined – $EV_i$ and $EV_e$. $EV_i$ represents a "communication line" for receiving messages from a charging station. On the other hand, $EV_e$ represents "energy line' which is used for charging the electric vehicle.

The *EVA* has three parameters – $E_{max}$, $E_{min}$ and $E_{CR}$. $E_{max}$ is the maximal electricity capacity of the vehicle. $E_{min}$ is the minimum level of electricity when the vehicle sends the request for charging to all stations. $E_{CR}$ represents the consumption rate per minute of driving. These parameters can be easily changed to simulate different scenarios.

Each *EVA* has two internal states – $P_{cur}$ and $A_{cur}$. $P_{cur}$ represents the remaining performance in the battery. When EVA is riding, $P_{cur}$ decreases about $E_{CR}$ per one minute. $A_{cur}$ is the current state of the *EVA* and it may be in one of the following four actions – Stop, Going, Charging or Waiting. The output interface is only one – $EV_{Out}$ which represents the communication interface used for sending messages from *EVA* to a charging station(s). The subsequent output connection is defined – $EV_o$ that represents a "communication line" for sending messages to a charging station.

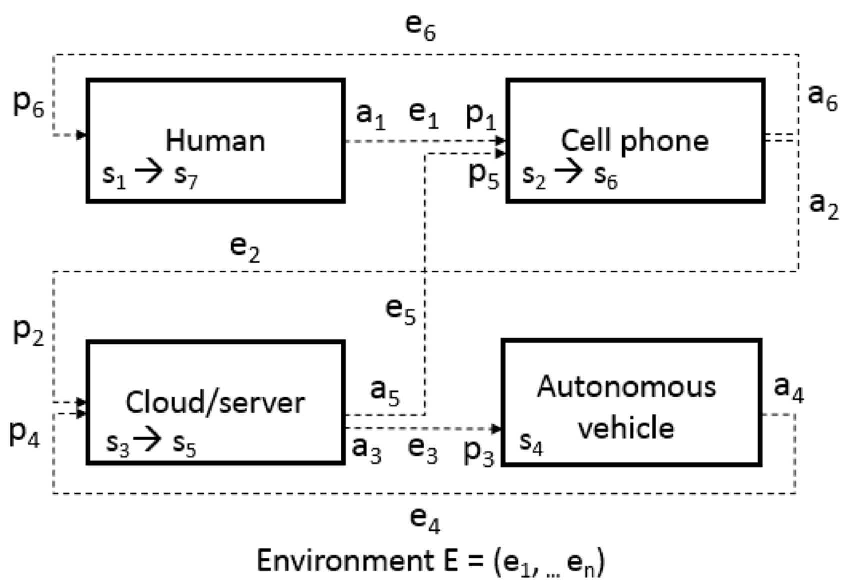


**Fig. 8.** An agent in its environment (Weiss, 2013).

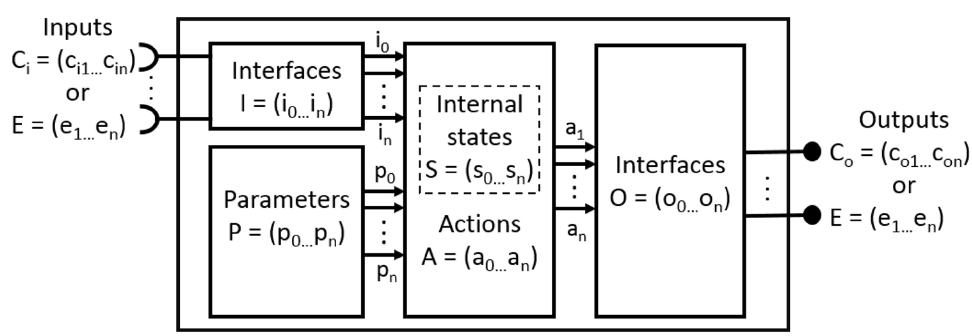


**Fig. 9.** The diagram of a Smart City Agent.

The Charging Station Agent (*CSA*) is designed in the same way as *EVA*. The diagram of *CSA* is shown in Fig. 11. The *CSA* has one input interface – $CS_{com}$ that represents the interface which is used for receiving messages from an electric vehicle(s). The subsequent input connection is defined – $CS_i$ that represents a "communication line" for receiving messages from *EVA*.

The *CSA* has three parameters – *PP*, *SP* and $P_{max}$. PP is the purchase price of electricity from energy network to a charging station. *SP* is the selling price of electricity to *EVA* from *CSA*. To generate a profit, *SP* must be higher than *PP*. $P_{max}$ represents the maximal performance which can be used for charging of *EVA*. Again, these parameters can be easily changed to simulate different scenarios.

The *CSA* has three internal states – $CS_{profit}$, $P_{del}$ and $A_{cur}$. $CS_{profit}$ represents the actual profit of *CSA* which is calculated as the difference between *SP* and *PP* (per kW). $P_{del}$ is the delivered performance which has been used for charging *EVA(s)*. $A_{cur}$ is the current state of the *CSA* and it may be in one of the following two actions – Waiting or Charging.

The *CSA* has two output interfaces $CS_{out}$ and $CS_{energy}$. $CS_{out}$ represents the communication interface used for sending messages from *CSA* to an electric vehicle(s). The interface $CS_{energy}$ is used for charging

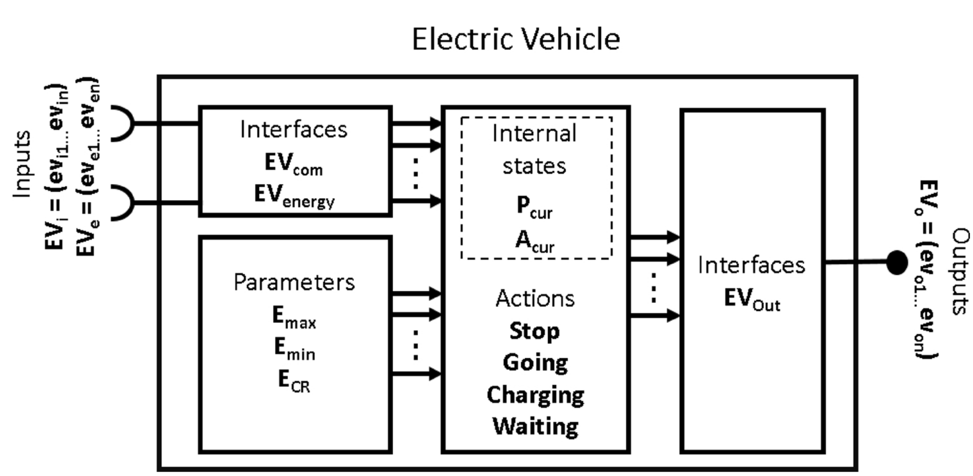


**Fig. 10.** Electric Vehicle as Smart City Agent.

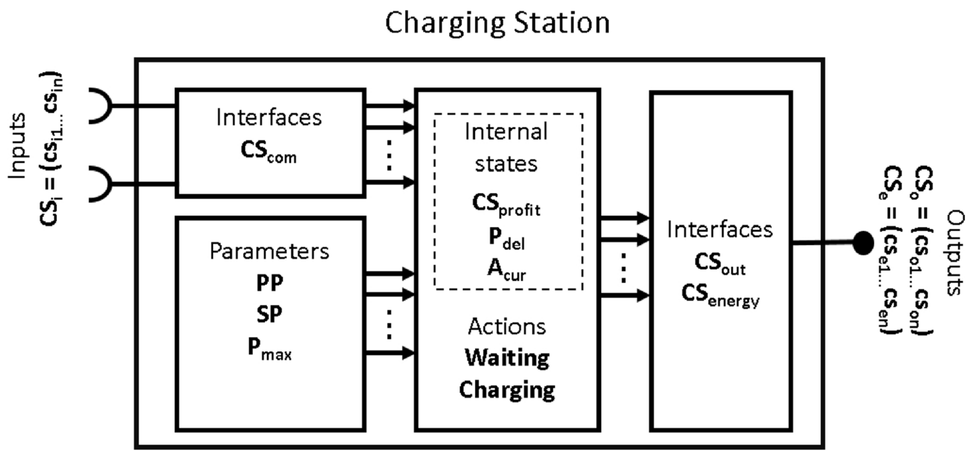


**Fig. 11.** The internal diagram of Charging Station Agent.

the vehicle by electricity from *CSA*. The subsequent input connections are defined – $CS_o$ and $CS_e$.

The final diagram showing the interaction between *CSA* and *EVA* is shown in Fig. 12. The process is started by *EVA* which sends a request for a charging. If any *CSA* is free, it confirms the request. If no *CSA* is free, *EVA* must wait in the queue. The last part of the process is a charging of *EVA*.

## 9. Results

The use case was implemented and evaluated as presented in (Lom & Pribyl, 2019). Even though it is not the most complex problem, it still

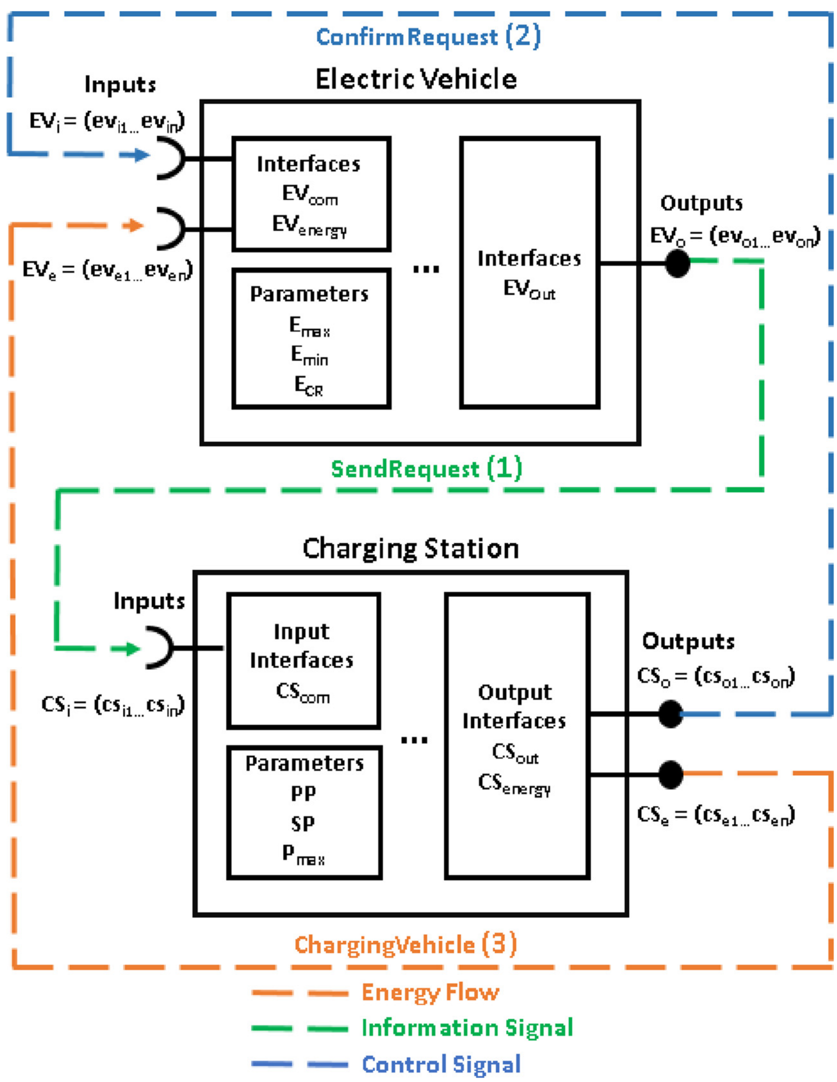


**Fig. 12.** The interaction diagram between CSA and EVA.

**Table 1**
An overview of the scenarios.

| | Charging time (min) | Capacity of battery (kWh) | Price of electricity |
|---|---|---|---|
| Scenario 1 | 30 | 50 | fixed |
| Scenario 2 | 30 - 60 | 35 - 60 | fixed |
| Scenario 3 | 30 - 60 | 35 - 60 | dynamic |

clearly demonstrates the usefulness of the proposed solution and lack of alternatives.

The simulation model was conducted for three different scenarios, always for the simulation time of 24 h. The number of charging stations is various as depicted in Table 1. All scenarios are executed 10-times and the average values of the indicators are calculated. No. of *EVA* is the maximum number of vehicles that can be located at one time at Charles Square. *MaxEVA* represents the maximum number of *EVA* in the queue. Maximum waiting time (*MaxWT*) represents the maximum time which some of *EVA* needs to wait for getting a free *CSA*. Mean waiting time (*MWT*) in the queue (min) means the average time which all *EVA* wait in the queue. The overview of scenarios is shown in Table 1.

The first scenario is our base lane. The charging time, the capacity of a battery and the price of electricity are all fixed. The second scenario still keeps the price of electricity fixed (similarly to scenario 1), but the charging time and the battery capacity have the distribution according to Table 2 (e.g. 40 % of EVA has the capacity of battery 50 kW h with the charging time 45 min). The third scenario enhances the complexity by using a dynamic price of electricity. Again, the charging time and the capacity of battery have the distribution according to Table 2.

The variations of the capacity of batteries have a significant impact on the mean waiting time in the queue as shown in Fig. 13. The dynamic price can additionally increase the mean waiting time in the queue as people want obviously use the opportunity to charge their vehicles cheaper.

The maximum number of *EVA* was generally achieved in scenario 3 ("cheap" price) as shown in Fig. 14. In this scenario, vehicles have the various capacity of batteries and also drivers want to charge their vehicles most preferably. On the other hand, the lowest number of *EVA* in the queue was achieved in the scenario 3 ("expensive" price) despite the fact that vehicles have variable battery capacity compared to the scenario 1. It shows that people are willing to wait extra time if they can save money.

This use case demonstrated some of the benefits of SMACEF and the interconnection of particular Smart City Agents. The different scenarios can be simulated and various alternatives are modelled to achieve optimal results under the dynamic characteristics within a city.

## 10. Discussion

Municipalities and agencies often face the need to select among various projects one, most suitable to solve a certain smart city need. Hashema et al. (Hashem et al., 2016b) identified the main challenges in addressing smart city projects as the planning phase: *"Building an integrated master planning and control methodologies of big data for the smart city is the main challenge encountered by smart city planners. Much of the information that must be addressed will require time and money to cost effectively meet the potential future requirements."* The first group of approaches tries to utilize multicriteria optimization and decision making. Wu et al. (Wu & Chen, 2019) proposed a method based on a combination of Modified Delphi Method (MDM), Analytic Hierarchy Process (AHP) and Zero-One Goal Programming (ZOGP). The authors stated its limitation as follows: *"Although the proposed model can be used in various situations, it is not only laborious to answer the AHP questionnaire but also difficult to confirm the consistency of the pairwise comparisons "*. Basically, this means that such approach does not capture the interactions and synergies among different subsystems. It is a simplified approach, based on panel of experts. The experts are provided with recommendations and criteria to assess the most suitable project.

**Table 2**
The distribution of EVA.

| % of EVA (%) | Charging time (min) | Capacity of battery (kWh) |
|---|---|---|
| 30 | 30 | 35 |
| 40 | 45 | 50 |
| 30 | 60 | 60 |

A natural solution to such limitations is in introducing simulation environments. Simulation is a generally accepted tool to assess impact of different measures and policies on a system (Antoniou et al., 2014). It is being successfully used in various fields, including transportation, energetics, business processes and many others (for example Hook, 2020; Jarrah, 2020 or Wunderlich et al., 2019). Simulation is well suitable for modelling of dynamic systems with many interactions. There is however a gap when we start to talk about really complex systems with many heterogeneous actors. A city is clearly an example of such complex system with many different overlapping subsystems.

### 10.1. Contributions to research

There is a need to have a simulation tool to estimate the impact of certain smart city strategies and to select projects to be implemented. The literature review revealed that there is no accepted model of a smart cities. There are basically two possible approaches to this task. First, usage of existing advanced models of partial domains and establishing a dynamic link among them (Přibyl, Přibyl, Lom, & Svítek, 2019); or creating a complex approach based on distributed heterogeneous agents and interactions among them (as proposed within this paper). Both of these approaches include several challenges and are not every explored. This is confirmed for example by Ismagilovaa et al. (Ismagilova, Hughes, Dwivedi, & Raman, 2019), who provided an extensive literature review in the field of smart cities. The authors point out that most of the studies within environmental or traffic category rely heavily on simulations to develop their findings. They identified several partial solutions, for example in the transportation or energy management fields. They have though not find a tool to simulate the smart city environment as a whole – which is the main contribution of this paper.

In general, simulation software typically requires a large amount of data. That is true also for the proposed solution. There is however a growing trend towards big data processing and the evolution of Internet of Things (IoT) technologies. This can be seen for example in the work of Hashem et al. (2016b). If we look at the Fig. 1 in their paper, a landscape of the smart city and big data technologies is provided. We can see clear parallel to the case study provided within this paper. They identify different actors, for example vehicles, parking spaces, or energy consumptions and production nodes. The authors claim that "*The key enabler of these smart city applications is possibly the IoT in which everyday objects and devices are connected to the network technologies*." We can only confirm that. While the authors focus on the technological perspective and the business model, we propose a modelling framework to assess tits effects in our paper. The authors provide a survey on the usage of big data and IoT in smart cities. Such data are needed to set up the simulation model and to calibrate it. This is a necessary synergic step.

The proposed approach addresses the issues mentioned above. While the results suggest its usefulness to model interactions in a heterogeneous environment, its main challenge will be certainly in so-called curse of dimensionality (Bai, 2014). This is a commonly known problem, especially in the field of artificial intelligence or soft computing. Having many different actors/agents, each acting in a certain space or dimension increases the overall complexity of the space.

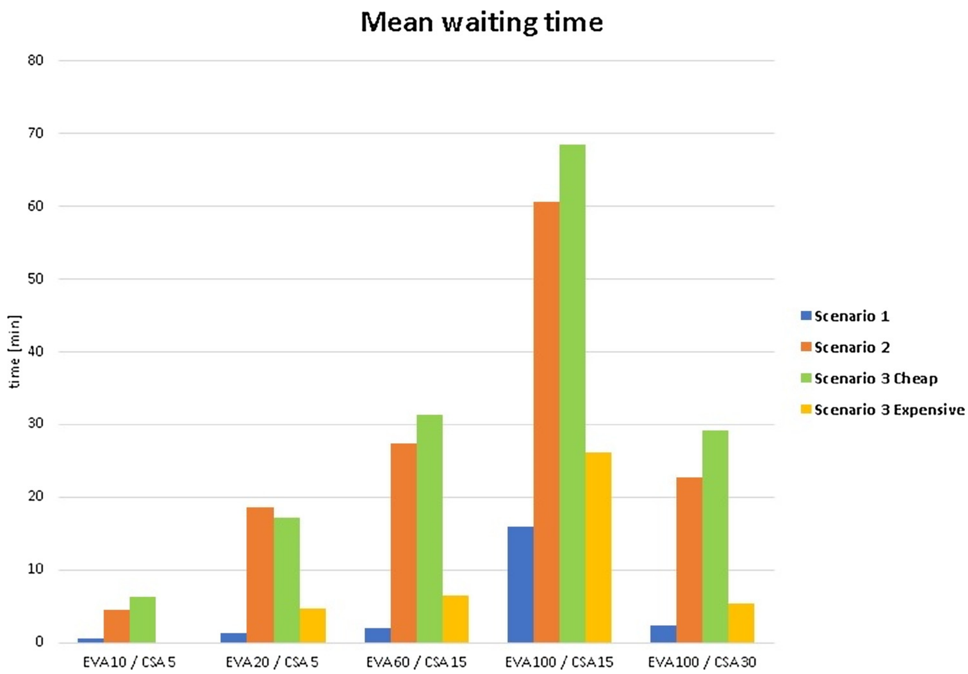


**Fig. 13.** The comparison of the scenarios based on mean waiting time.

However, the proposed multi-agent approach has the potential to distribute the intelligence in a way not to model the overall multi-dimensional space, but limit it to the environment of each agent separately (of course when keeping in mind its interfaces). This however requires a commonly agreed meta-model covering the domain knowledge base. Ontology has been identified as a key to standardize the knowledge management and information exchange. M. del Mar Roldán-García, et al. (del Mar Roldán-García, García-Nieto, Maté, Trujillo, & Aldana-Montes, 2019) used the ontology-driven approach to formally conceptualize essential elements of performance indicators in smart cities. When talking about heterogenous and distributed agents, ontology has been identified as a key to multi-agent systems and is thus a natural extension of the approach described in this paper (Obitko & Mařík, 2020).

### 10.2. Practice and limitations

In order to demonstrate the proposed framework, a case study dealing with charging of electrical vehicles was provided. Similar problem was addressed for example by Gellerta et al. (Gellert, Florea, Fiore, Palmieri, & Zanetti, 2019). In their work the authors used Markov chains, stride predictors and also their combination into a hybrid predictor in modelling the evolution of electricity production and consumption in buildings. Such prediction uses historical data and unfortunately does not take into consideration interactions and other factors influencing consumption. The authors claim that the effects of a technology-induced reorganization of the smart grid when users no longer are passive participants in the relationship between them and the infrastructure, but they become active and the information flow

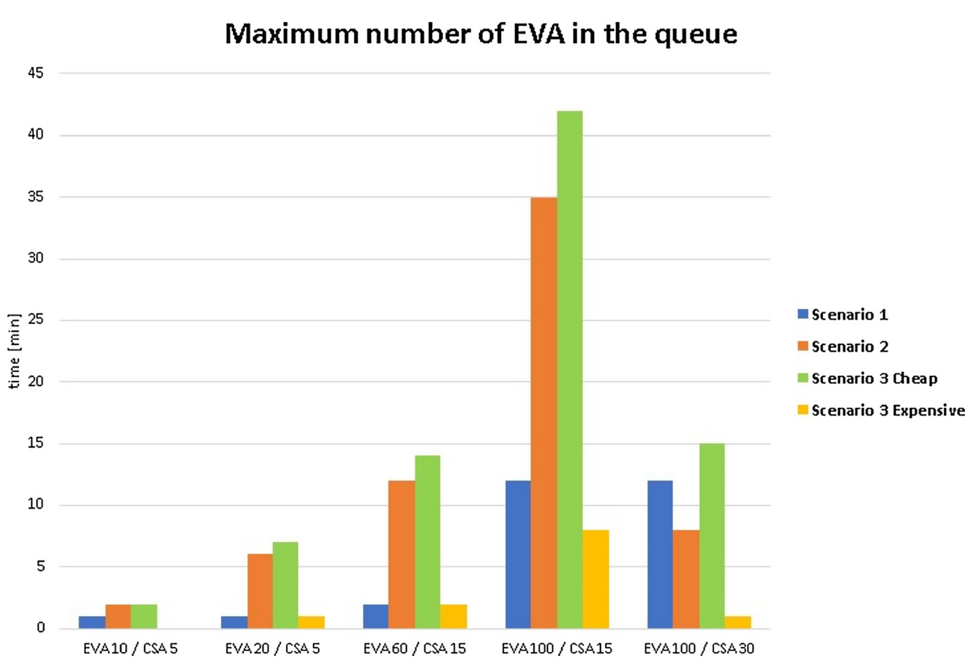


**Fig. 14.** The comparison of the scenarios based on maximum number of EVA in the queue.

becomes bidirectional, can be profound and should be studied with great attention. Such prediction is, though, centralized. And this is exactly what the proposed simulation framework aims to achieve. The effects of different actors can be evaluated. The multi-agent system is by default of a distributed nature, exactly as the case study requires. When combined with the prediction mechanism suggested for example by Gellerta et al. (Gellert et al., 2019), on the input data, a future (predicted) impact of the distributed and interconnected environment can be achieved.

We believe that the proposed solution is a key to further development of a simulation tools in the field of smart cities. In order to utilize it even further, it is recommended to base the multi-agent solution on a domain ontology. Also, it will work best with the calibration data collected by IoT technologies.

## 11. Conclusions

In this paper, the area of smart city modelling is classified to the theories of Systems Theory and Cyber-Physical Systems. First, a smart city can be generally seen as an environment according to the Systems Theory, and particular systems (energy, buildings, transportation) within the smart city can be seen as systems. These systems can be divided into subsystems. The biggest difference between traditional cities and smart cities is that systems interact only with their environment in traditional cities. It means that systems are mostly stand-alone and not interoperable with other systems. In smart cities, systems are interconnected by energy or information relations, and information management becomes more and more important.

Second, the specific area of the Systems Theory is Cyber-Physical Systems where physical (hardware) and virtual (software) worlds are interconnected. Data from physical world are sent to virtual world where are analysed and appropriate actions are performed.

Third, the Systems Theory and Cyber-Physical Systems can be modelled by Multi-Agent Systems. A Smart City Agent as a building block for modelling smart cities is introduced in this paper. The Smart City Agent is a modified version of an intelligent agent. It is more suitable for benchmarking and evaluating purposes in smart cities. The practical example of an implementation of Smart City Agents using SMACEF is demonstrated. The novel approach is demonstrated in this paper as cities are dynamic and nonlinear systems. For this reason, the models have to be dynamically simulated with different scenarios, and the results of these simulations can be benchmarked. For the future work, the authors suggest to implement more complex Smart City project and discover the benefits of interconnecting system and sharing data and information.

### *11.1. Future research directions*

The proposed solution can be directly used by practitioners to model dynamic behaviour of interacting subsystems. The literature review shown that at the present, there is no alternative solution to this task and city representatives are depending on the providers of partial solutions. At the same time, it is recommended for researchers to elaborate on the internal logic of particular Smart City Agents to further detail the behavioural characteristics of particular subsystems as well as the management of information exchange.

As a natural next step, a bigger and more complex case study (particularly modelling of Vitezne square in Prague 6) will be developed. It shall not only demonstrate feasibility of the framework, but address the real world issues, for example an impact of new building in the area. It will be used in a project *City simulation software (CSS) for modelling, planning and strategic assessment of territorial city* units supported by the Technology Agency of the Czech Republic. Here, it will be coupled with outputs from research groups dealing with dedicated models for environmental (e.g. spread of emissions), transport as well as modelling of energy consumption. As part of the project, an ontology will be developed to solve the issues described in Section 10.1 and to allow the agents communicate with each other.

## CRediT authorship contribution statement

**Michal Lom:** Conceptualization, Methodology, Software, Writing - original draft. **Ondrej Pribyl:** Conceptualization, Data curation, Writing - review & editing.

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