Chapter 14
Smart Cities: Distributed Intelligence or Central Planning?

14.1 Introduction

Cities were always smart. In every era, advanced technologies and innovative thinking have developed in cities; from the written word 5000 years ago; to the revolutionary Greek concepts of democracy and citizenry; to Renaissance art and architecture; to the factories of the industrial revolution; to today’s post-industrial age of high technology. (Portugali 2016a)

This leads us to the question whether there is a specific feature that distinguishes the present days’ concept of a “smart city” (Batty et al. 2012) from those of history. We think that a clue to answer this question is a look at our present most frequent use of the word “smart”. In fact, we speak of smart phones, but also of smart houses, smart households, smart cars etc. At a still larger scale, smart factories are conceived. These smart objects are related to the notion of The Fourth Industrial Revolution (Schwab 2016) suggesting that today once again society is at the threshold of an industrial revolution: The 1st happened in the eighteenth century by the introduction of mechanical machines, the 2nd in the 2nd half of the nineteenth century via electrification. The 3rd revolution is characterized by computers and microelectronics, while presently we witness the rise of smart factories by what is called “digitization” of a network comprising construction, development, production, sales, and services (cf. Bauernhansl 2015). This implies an integration between real and virtual worlds, enabling the simulation of systems, processes and even complete factory plants in real time. Here, the reconciliation between long term planning and short term reactions to customers’ wishes and market fluctuations presents a real challenge. Planners presently consider the human–robot cooperation from the point of view of a combination of the cognitive superiority and flexibility of humans and the power, endurance and reliability of robots. Quite evidently, the concept and development of smart cities will present a far greater challenge that has to take care of the central task of a city—the welfare of its citizens.
The currently developing discourse on smart cities is intimately associated with CTC (complexity theories of cities) that we’ve discussed in Chap. 2. Smart cities with their massive use of AI/IT are considered as one central way to cope with the growing complexity of cities, while the set of urban simulation models developed within the context of CTC is considered one among the new ICT (information communication technology) that enables the smartification of cities (Batty et al. 2012).

As we indicate in Chap. 2, while cities share many properties with natural complex systems, they differ from the latter in that they are hybrid complex systems composed of artifact that are by definition simple systems and of human urban agents that are natural complex systems. In today’s cities there is a clear distinction between the artificial components of cities as hybrid complex systems (e.g. houses, streets, etc.) and their natural components—the human urban agents. Artifacts cannot interact (exchange things/information), agents can. Artifacts interaction is thus mediated by agents. Also, a lot of agents’ interaction is mediated by artifacts (cf. Chap. 4). With AI/IT, artifacts might be able to interact directly with each other without mediation by human agents and thus become artificial urban agents. E.g. a self-driven car can interact with a self-organized traffic light in a junction. Artifacts thus become urban agents giving rise to a new form of urban dynamics. Part of it may be smart traffic regulations (guiding system), smart supply systems of energy, food, goods, or smart waste disposal. But nevertheless: Who or what is smart?

The technical installations (houses, communication systems, supply systems), their human planners and users, or their interplay? At any rate, we are facing a delegation of human decision making and responsibilities to automata. So all in all we believe that “smart city” implies a qualitative change based on AI (artificial intelligence) embodied by IT (information technology) on all scales. This means that we must not ignore the fact that cities are embedded in nations in an increasingly connected global world which is becoming also “smart” using AI (just think of the financial market with its computer controlled transactions). At all levels, there will be a demand for sensors, actuators and computing power. The wide use of AI/IT devices will lead to an innovation wave quite welcome to economists because innovations are seen as a motor of economic growth and public welfare. In the following we want to elucidate some aspects of “smartification”.

Basically, we may distinguish between two approaches: The top down approach, where data are collected locally and sent to a central computer, which makes the decisions, or a bottom up approach where the decisions are made at the individual level based on collected data. The latter approach is outlined in a study by Feder-Levy et al. (2016), based on Portugali’s concept of self-organizing city (Portugali 2000, 2011, 2012). As we’ve seen in previous chapters (specifically Chaps. 3, 5 and 6) the theory of Synergetics offers an integrative approach: Local bottom–up decisions and actions give rise to a collective structure that then in a top–down manner determines (“enslaves”) local actions and decisions and so on in circular causality.

In the beginning, solid structures such as houses, streets, will probably not be changed. Only at a later stage, changes may become necessary due to a newly developing dynamics of traffic, but also of personal habits. E.g. as is evident in the new reality of the corona pandemic, IT has the potential to lead to a delocalization of
teaching and, perhaps, education, by replacing schools and universities by tele-courses, e.g. MOOC (massive open only courses). Because this implies a loss of personal contact between teachers and students (and among students) it is, however, unlikely that schools and universities will disappear completely. The same holds true for sports—or cultural centers. Can e.g. in a baseball or soccer game virtual reality replace the feeling of being member of some community?

### 14.1.1 On the Interplay Between Humans and Smart Devices

Smart devices on nearly all scales will replace human senses and (re)actions. A few examples may illustrate this. In a smart home sensors may measure the actual amount of daylight/sunshine, rain fall, in- and outdoor humidity and temperature, energy consumption etc. In a city, sensors may measure local traffic flows, local and overall energy consumption etc. So far in a home, individuals have reacted to the data, e.g. temperature according to their specific habits. Now, “AI-devices” learn all these human reactions, e.g. to close the venetian blinds at a certain level of sunshine. But there may be conflicts between family members. While A wants them to be closed, B wants them to remain open. This learning problem can perhaps be solved by some kind of majority decision based on relative frequencies of action. At any rate the AI device will then act instead of a person. This is surely convenient for the individual, but leads also to a reinforcement of his/her habits, i.e. his/her habituation.

From the point of view of the complexity theory of Synergetics, the above situation implies that the AI program has become the order parameter (OP) that now, in the literal sense of the word, enslaves the individuals. Having the properties of OPs in mind, it will be difficult to change that OP. Such habituation effects have been repeatedly discussed in connection with advertisments based on consumers’ behavior. At the political level, even some kind of nudging has been discussed.

A down to earth technical problem should be mentioned when WLAN is used in neighboring flats/homes, interference effects may spoil the operations. Both, conflicts of interests among citizens as well as habituation may occur at the city level: chosen car routes (think of autonomous cars interacting with traffic guidance systems), total energy consumption, use of communication channels, supply routes for commodities etc.

While in this way, the former more or less self-organized collective behavior of the citizens will be learned by the AI system and “regulated” correspondingly we may think of quite another scenario: a central city computer tries to solve a multi-travelling salesman problem. Though we don’t know how such an approach would look like or what its results/efficiency will be, such a scenario is by no means unlikely. This may perhaps lead to large computer centers outside cities where building sites are cheap. Finally, centralized installations will increase the vulnerability of cities against crime, terror acts and global break down. Other basic problems are, e.g. energy consumption control. A typical “recipe” runs like this: increase/decrease of energy price over the day/night depending on consumption thus influencing the consumers’ action. As is
well known this scenario may lead to instabilities in the network. A stricter central control may eliminate the instabilities, but will curb individual freedom: clearly, smartification has sociological implications.

14.1.2 Theoretical Tools

To study implications of “smartification” from the point of view of theory, we have a number of approaches at hand, i.e.

(1) Cognitive Science
(2) Artificial intelligence
(3) Information theory
(4) Synergetics
(5) Network theory
(6) Multi-agents theory
(7) Evolutionary game theory
(8) Allometry/Scaling laws
(9) Biology—Evolution, population dynamics

Besides these approaches with their roots in mathematics and the (natural) sciences, other disciplines will play a role in smart cities such as.

(a) jurisprudence (e.g. responsibility transfer, liability)
(b) sociology (e.g. job market requiring highly qualified personal for IT-maintenance, development of AI/IT, but also disappearance of other jobs, e.g. taxi drivers, bank clerks etc.)
(c) psychology (e.g. psychological stress in an automated world)
(d) political science (e.g. decision making on cities’ smartification in a democratic society)
(e) economics (e.g. investments in smartification)
(f) ecology (e.g. management of resources by smartification)

Having said this, we focus our attention on some of the topics 1–9. First we briefly discuss them. Since, at least according to our understanding, “smart city” implies a massive use of AI/IT, a discussion on intelligence in general and on AI in particular may be in order. Here, we have to draw on insights gained by Cognitive Science. We will elaborate this in Sect. 14.2. In this context, we will briefly discuss information theory and its more recently established connections with cognition such as information adaptation (cf. Chap. 4).

Cities with their inhabitants, and mobile and immobile installations (artifacts) are truly complex systems that form specific spatial and functional structures where the interplay or competition between central planning and local personal initiative becomes quite decisive (Chaps. 2 and 15). A general theory of structure formation in complex systems is provided by Synergetics that we have outlined in previous
sections. This will shed light on the role of indirect steering in contrast to conventional planning. Network theory (cf. e.g. Barabási 2016) gives insight into the links, e.g. between inhabitants or between neighborhoods or cities, and allows, e.g., the derivation of scaling laws. On the other hand, multi-agent theories (cf. e.g. Bretagnolle et al. 2006; Roscia et al. 2013) deal with the actions of citizens and automata. Quite clearly, network theory will play an important role in IT dealing with communication and transport. In the context of this chapter we are rather concerned with AI aspects. Evolutionary game theory (EGT) deals with the benefits of cooperation between partners (persons, companies, institutions etc.). The concept of Nash equilibria (well known in EGT) will play a role in our discussion. EGT originated from game theory developed by von Neumann and Morgenstern (1944). The biological concept of evolution, in particular based on mutations, has become an important ingredient of EGT (e.g. Nowak 2006). Mutations are treated as chance events, also denoted as fluctuations. As is shown quite generally in Synergetics, fluctuations play a fundamental role in the selforganized formation of structures. Fluctuations can be also considered as means to test the stability or resilience of a system against perturbations and to trigger novel developments. A further line of research inspired by biology is allometry which is being applied to theories on city growth. In biology it was found that e.g. the age, size, blood flow and other characteristic features of animals scale with body weight $w$ by means of a power law, $\propto w^{l/4}$, $l = 1, 2, 3$ (West and Brown 2005). Similar laws have been considered in the case of cities (Bettencourt et al. 2007). We will discuss such laws with respect to “smart city” at several instances below (Sect. 14.5).

### 14.2 Intelligence

Having in mind that “smartification” implies the application of AI to cities, a few remarks on intelligence may be in order, at least what its role in cities concerns. Most probably, it is sufficient to deal with intelligent behavior. This in turn means: appropriate actions, or depending on the specific situation, reactions. A prerequisite for these processes is pattern recognition, where “pattern” may be interpreted in a wide sense, e.g. as images of faces, or objects, or whole scenes, or movement patterns of persons, groups of them, of traffic, or just a set of measured data, e.g. temperature distribution in a home or in a city. The central problem consists in the selection/Recognition of features that are/will be relevant for (re)action and to draw the relevant conclusions. To have the required actions quickly at hand, a whole repertoire of (re-)actions must be learned in advance. A number of them may be based on planning, and foresight is required. An important problem is the challenge of new situations to decision making. In many cases, people base the latter on more or less justified analogies with previous experience by extrapolating (“heuristics”). But in a number of cases, entirely new solutions (actions) are required. Among such chance events are technical failures, human mistakes, natural catastrophes, but even new state laws etc.
So far we have spoken of intelligent behavior of an individual. But there is also collective intelligence. The famous economist Friedrich August von Hayek spoke of “intelligence of the market” which in the present context can be extended into the “intelligence of the city”. Some collective intelligence is even attributed to swarms of birds or schools of fish. Quite a number of scientists think that collective intelligence cannot be substituted by individual intelligence. At least one of the reasons is the “information bottleneck”: a central agency, or even an individual, cannot deal with the huge amount of incoming information. Thus only delocalized decision making (by the market) is possible. Clearly, there is a dichotomy between local initiative and global planning. Coming back to “smartification”. Taken seriously, it means the replacement of human intelligence—as sketched above—by artificial, that is, machine, intelligence.

14.2.1 Artificial Intelligence (Machine Intelligence)

Here we don’t discuss philosophical issues such as the “ghost in the machine” nor ethical, such as responsibility or liability of machines. But cf. e.g. Bonnefon et al. (2016).

The first step consists in the collection of data by sensors for optical, acoustic, chemical, tactile, acceleration etc. signals. Present days’ data may be enormous; hence the notion of “big data”. If not appropriately preselected (“filtered”) they mirror a complex world. The next, in our view decisive step is supervised learning (cf. e.g. Le Cun et al. 2015). For example, in image recognition, a huge number of faces of the same person but in different positions, under different illuminations is presented to the computer that has to “learn” that all these images are associated with the name of that person. This is accomplished by an algorithm with a huge number of adjustable parameters. This procedure is usually visualized as a feed-forward net with a considerable number of layers (say 20–100). Most of the adjustment procedures are based on the method of “steepest descent”. To get an idea what this means and implies, think of a landscape with mountains and valleys in between. The bottom of each valley represents a specific prototype pattern to be recognized due to given data which are represented by the position of a stone in this landscape. Since in general the data are incomplete or/and partially erroneous, the position of the stone does not precisely coincide with that of the bottom of the relevant valley. But the stone can correct this error by sliding downhill.

This little side remark may shed light on a basic problem: how certain is it, that the “envisaged” valley is the correct one? This also implies that under somewhat changed conditions, the previous valley is no more the appropriate one if it has happened so before. This means there is no guarantee for the adaptability or generalization capability of this algorithm. Besides such a rather superficial consideration (and related ones) there is no theory of such networks that would allow us to understand the learning process. In a way the whole learning procedure is reminiscent of the training of animals. We don’t know, what happens in their brains. And perhaps, once the tig
bites, quite unexpectedly. An additional remark may be in order: at least at present, the training time of such a network is days, which may be shortened by the parallel use of thousands of computers. Nevertheless, the speech recognition capability of systems such as Siri (Apple) is impressive. So far we have talked about recognition (which in case of AI may include that of scenes and of actions of persons). What about action of automata? The same way as recognition can be “taught” to a computer, it can also be taught to steer movements of actuators in particular by imitation. But then, quite often, the machine is confronted with a conflict situation: which movement to steer (perform)? The inability of the machine to make an autonomous decision leads to deadlock. In human life, in such a situation a deeper insight, or deeper experience is required and helps to overcome the deadlock. On the other hand, if such a conflict situation hasn’t been “shown” to the machine—deadlock results.

14.3 Information Dynamics and Allometry in Smart Cities

In Sect. 10.5 we have dealt with information production (and processing) in “traditional” cities, based on the notions of SHI, SI and PI. These notions and their relations in connection with cities, were introduced in Chap. 4 in the context of SIRNIA. Here our aim is to apply them to the smartification of cities. We briefly remind the reader of our approach of Sect. 10.5. Humans (“agents”) play a double role: they receive information and produce information. We assume that the received information is of Shannon type and the “produced” information of pragmatic type. The latter leads to observable actions of the agents. As we show in some detail in Chap. 4, because of their recognition capabilities the agents transform the data emitted by the environment firstly to SHI and then into PI. For simplicity, in what follows we’ll deal with the conversion of SHI into PI. Let us consider the role of the city that is composed of artifacts and agents. Both emit signals (e.g. the artifacts in Gibsonian language as affordances). All these signals are treated as “raw material” in form of SHI that has then to be “deciphered” by the agents i.e. converted in PI.

Thus SHI is the number of bits produced by a city, e.g. per day, and embodied by letters, on monitors—a gigantic, but nevertheless measurable number. These signals are received, filtered and interpreted by the human sensorium and eventually converted into PI. This leads us to our model depicted in Fig. 14.1a. As can be seen, Fig. 14.1 illustrates graphically four stages in the smartification of a city, starting from Fig. 14.1a, representing the current state of cities, all the way to Fig. 14.1d that represents a “fully smart” city as discussed in more detail, below. The four stages in the smartification of a city are:

(a) The city and its human inhabitants exchange information. While the city produces SHI, its human inhabitants recognize these signals and convert it via PI into actions
(b) Automata participate in the exchange process
Fig. 14.1 Stages of smartification (cf. also text). In the case of automata dominance $a^2r_ar'_a/\gamma_a \gg n^2r_hr'_h/\gamma_h$ (cf. Sect. 14.6)

(c) The direct action of humans on the city has practically disappeared and is mediated by automata
(d) Automata are perceived by humans as part of the city.

Now we focus our attention on the role played by automata. Our basic approach is depicted in Fig. 14.1. We distinguish between three producers and processors of information: the city as a whole comprising artifacts (buildings, streets, etc.), human agents, and automata (artificial agents). We treat the city as a sender of information (where the role of artifacts is interpreted in Gibson’s sense of affordances). According to SIRNIA (Chap. 4, Fig. 4.9), the emitted information is treated as SHI and measured in bits. Its recognition is left to the receivers, i.e. to humans and automata. Thus according to our previous analysis, SHI is converted into PI (and SI). PI becomes visible as specific actions performed by humans and automata. Actually, pattern recognition capabilities are ascribed to the latter, as well as the capabilities of appropriate reactions. We include SI (semantics) in PI, provided ideas, concepts, plans, etc. (“mental states”) are externalized, e.g. by written texts, computer programs, including those for graphics, etc. (see also the concept of SIRN). We measure PI in bits. Since in our approach we are dealing with grossfeatures to illuminate the impact of automata on information we consider the total amount of SHI and PI per 24 h in a city. We assume an unlimited channel capacity. Clearly, more IT oriented approaches will have to consider the effect of channel capacity also. We assume that
the conversion of SHI→PI occurs within 24 h (“temporal course graining”) and we ignore the local fine structure (“spatial course graining”). We treat the city as an open system with imports and exports of raw material, commodities, ideas etc. The variables of our basic equations are

- SHI produced per day by the city, denoted by $s$.
- PI produced per day by humans, denoted by $p_h$.
- PI produced per day by automata, denoted by $p_a$.
- $n$ is the number of citizens.
- $a$ is the number of automata.

In the spirit of Synergetics, $s, p_h, p_a$ are the order parameters while $n$ and $a$ act as control parameters jointly with rate constants defined in the following.

We come to the formulation of rate equations

**p-rates**

1. generation rate of $p_h$ (by human actions) $\frac{dp_h}{dt} \big|_1 = n \cdot s \cdot r_h$: humans transfer incoming Shannon information into PI$_h$ (actions) at rate $r_h$
2. generation rate of $p_a$ by automata $\frac{dp_a}{dt} \big|_1 = a \cdot s \cdot r_a$: automata transfer incoming Shannon information into PI$_a$ (actions) at rate $r_a$
3. loss rate of $p_h$ $\frac{dp_h}{dt} \big|_2 = -\gamma_h p_h$
4. loss rate of $p_a$ $\frac{dp_a}{dt} \big|_2 = -\gamma_a p_a$ loss because of forgetting, executed actions by humans or automata, storage in memory.

**s-rates SHI is produced by the city**

5. generation rate of $s$ $\frac{ds}{dt} = $ generated data $D$
6. by humans $D_h = n \cdot g_h + n r'_h p_h$, $g_h$: spontaneous generation rate per human, $r'_h p_h$: stimulated actions per human
7. by measurement devices $D_a$ (automata) e.g. energy consumption, traffic flow $D_a = a g_a + a r'_a p_a$, $g_a$: generation rate per automaton, $r'_a p_a$: stimulated action per automaton
8. loss rate of $s$: $\gamma_e s$, where $\gamma_e$ error rate
9. by conversion $s \to p_h$: $\tilde{r}_h s n$ (via humans)
10. by conversion $s \to p_a$: $\tilde{r}_a s a$ (via automata)
11. by errors, $\gamma_e s$, where $\gamma_e$ error rate
12. by spam, chunk included in (11) total rate $s$
13. $\frac{ds}{dt} = n \cdot g_h + a g_a + n r'_h p_h + a r'_a p_a - \tilde{r}_h s n - \tilde{r}_a s a - \gamma_e s$

We consider the steady state

14. $\frac{dp_h}{dt} = \frac{dp_a}{dt} = \frac{ds}{dt} = 0$

The sum of the generation rate (1) and loss rate (3) jointly with (14) yields

15. $n s r_h - \gamma_h p_h = 0$

Similarly, (2), (4), (14) yields

16. $a s r_a - \gamma_a p_a = 0$

The sum over (6), (7), (9), (10), (11), jointly with (14) yields
These three equations for $s$ and $p_h$, $p_a$ depend, in particular, on the parameters $n$ (humans) and $a$ (automata).

Solution to (17):

\[ s = (\tilde{r}_h n + \tilde{r}_a a + \gamma_e)^{-1} (n g_h + a g_a + n r_h' p_h + a r_a' p_a) \]

Solution to (15) and (16):

\[ p_h = \gamma_r^{-1} n s r_h \]
\[ p_a = \gamma_a^{-1} a s r_a \]

from which we obtain

\[ p_h / p_a = \gamma_h^{-1} n r_h / (\gamma_a^{-1} a r_a) \]

or, equivalently

\[ p_a = A p_h, A = \gamma_a^{-1} a r_a / (\gamma_h^{-1} n r_h) \]

and with (18)

\[ p_h = \gamma_h^{-1} n r_h (\tilde{r}_h n + \tilde{r}_a a + \gamma_e)^{-1} (n g_h + a g_a + n r_h' p_h + a r_a' p_a) \]
\[ p_a = \gamma_a^{-1} a r_a (\tilde{r}_h n + \tilde{r}_a a + \gamma_e)^{-1} (n g_h + a g_a + n r_h' p_h + a r_a' p_a) \]

Inserting (24) in (23) yields

\[ p_h = B(C + D p_h) \]

and thus

\[ p_h = (1 - BD)^{-1} BC \]

$B, C, D$ are defined by

\[ B = \gamma_h^{-1} n r_h (\tilde{r}_h n + \tilde{r}_a a + \gamma_e)^{-1} \]
\[ C = n g_h + a g_a \]
\[ D = n r_h' + a r_a' A, \]

or, with (22)

\[ D = n r_h' + \frac{a^2 \gamma_a r_a' A}{n \gamma_a r_a} \]

The solution (26) requires

\[ (1 - BD) > 0 \]

because $p_h > 0$, and $BC > 0$.

$(1 - BD) = 0$ means that no steady state solution exists in contrast to the assumption (14). In this case the complete time-dependent equations must be considered which lead to instability.

This instability is caused by a feedback loop $SHI \rightarrow PI \rightarrow SHI$ inherent in our (time-dependent) equations. In the spirit of allometry, we are interested in the functional dependence of $p_h$ (humans) and $p_a$ (automata), i.e. human and automata activities, on parameters, in particular number $n$ of citizens and number $a$ of automata, and rate constants. In the conversion rates $r_h, r_a, \tilde{r}_h, \tilde{r}_a$ for each individual human or automaton, a number of preselection constraints enter, such as special kinds of transmission channels, their network structure, wired, wireless etc. For our analysis it will be sufficient to discuss the relative size, at least of some pairs of rate constants. The rate $r_h$ determines the information transfer from SHI (city) to PI (humans), while $\tilde{r}_h$ the information transfer from PI (humans) to SHI (city). Their relative size can be determined as follows. We consider these processes ignoring all other processes. Then according to (1) and (13) we obtain for their sum.
\[
\frac{d}{dt}(s + p) = (r_h - \tilde{r}_h)s \\
r_h - \tilde{r}_h = 0 \text{ means that } s + p = \text{const.}
\]

Here we can draw on our previous work where we have introduced the notions of deflation and inflation meaning here

\[
\frac{d}{dt}(s + p) < 0 \text{ (deflation), } \frac{d}{dt}(s + p) > 0 \text{ inflation.}
\]

(34) In practice, we expect deflation, which means \( r_h < \tilde{r}_h \) (at least on average).

The same conclusion holds true for automata,

\[
r_a < \tilde{r}_a.
\]

The size of \( r_h(r_a) \) is a measure of the ability of humans (automata) to convert SHI into PI, i.e. to recognize signals and to convert them into action. At present, surely \( r_h \gg r_a \), but the concept of a “truly” smart city might imply \( r_a > r_h \). In view of the big progress made in computer linguistics, the experimental determination of the transfer rates \( r \) per human (or automaton) where \( r \) may depend on the finite range of included topics is in our opinion possible. The \( r \)s we use in our eqs. are average values over many humans (automata) relevant for city life (including “import”, “export”). Little can be said about the decay rates \( \gamma \), but surely \( \gamma_e \) will increase in the course of time because of spams etc. When dealing with smart cities we must be careful when comparing the rates \( r_h, \tilde{r}_h \) with \( r_a, \tilde{r}_a \), because our use of the word automaton may comprise a wide range of interpretations—from smart household devices over robots till large computer centers. So when we consider special cases, we will have to take these distinctions into account. In particular, when computer centers play an important role, we have to compare the combinations \( r_hn, \tilde{r}_hn \) with \( r_ana, \tilde{r}_ana \). Finally we have to discuss the inclusion of export and import of material and immaterial goods. The effect of import (or “input”) can be taken care of by extending the interpretation of \( D_h \) (6), \( D_a \) (7). In (6), we may replace the spontaneous generation rate \( g_h \) by

\[
g_h = g_{hc} + g_{hi}
\]

where \( g_{hc} \) is just the former spontaneous rate, whereas \( g_{hi} \) is the generation rate of SHI induced by imports. Similarly, we may proceed with (7), by making the replacement.

\[
g_a = g_{ac} + g_{ai}
\]

Note that, at least at the present state of AI, we may put

\[
g_{ac} \approx 0,
\]

because we assume that AI-devices can hardly produce truly novel ideas. The rate of export, \( E \), can be expressed by \( E = r_{he}p_h + r_{ae}p_a \) with the rate constants \( r_{he}, r_{ae} \). In our approach, the SHI, PI dynamics is not directly influenced by \( E \), but indirectly via the loss rates \( \gamma_h, \gamma_a \). While clearly our model refers to a whole city and all its activities, a number of similar models can be established to deal with specific issues. Just to mention a typical example: humans observe (“measure”) the walking speed of other humans (SHI) and respond by adjusting their own speed (PI) taking into account other relevant features of the city, in particular its size (e.g. Haken and Portugali 2016).
14.4 Special Cases Giving More Insight

In this section we discuss the dependence of $p_h$ on the various parameters, particularly on $n$ and $a$ but also on the rate constants $r$. The special cases we treat are characterized either by the dominance of human activities over those of automata (case $h$), or vice versa (case $a$). Our starting point is (26) with its quantities $B$, $C$, $D$ (27–30). The just mentioned cases ($h$, $a$) can best be distinguished by means of $D$ (30). Multiplying (30) by $n r_h \gamma_a$ we obtain on the r.h.s. a sum of

$$D (30) \text{ reduces to } D = n r_h'$$

and

(39) \( h \ n^2 r_h r_h'/\gamma_h \) that refers to human “attributes” and

(40) \( a^2 r_a r_a'/\gamma_a \) that refers to automata “attributes”

According to \( h \gg (a) \) or \( (h) \ll (a) \), we derive simplified expression for $p_h$.

First we assume

$$B = \gamma_h^{-1}$$

so that

(41) \( B D \approx n \frac{r_h'}{\gamma_h} \)

Putting (26), (41), and (28) together, we obtain for the “load” per person

$$p_h/n \approx \left( 1 - n \frac{r_h'}{\gamma_h} \right)^{-1} \gamma_h^{-1} \left( g_h + \frac{a}{n} g_a \right)$$

where the impact of the term $\frac{a}{n} g_a$ is, in the frame of our approach, negligible.

Most remarkable is the factor $\left( 1 - n \frac{r_h'}{\gamma_h} \right)^{-1}$ which causes an enhancement of the spontaneous “production rate” $g_h$. This factor may lead to an instability, when $\left( 1 - n \frac{r_h'}{\gamma_h} \right) = 0$ which may be possible for a sufficiently large population.

In this case, no steady state of PI (and SHI) is possible. (See below). In the context of smart city, the case of the dominance of automata (a) is still more interesting, where \( (h) \ll (a) \).

We assume $\tilde{r}_a \approx r_a$ and obtain.

(44) \( B = \gamma_h^{-1} n r_h (r_a a)^{-1} \)

(45) \( D = a^2 r_a r_a'/\gamma_a (n \gamma_a r_h)^{-1} \)

so that

(46) \( B D = a r_a'/\gamma_a \)

Putting (26), (28), (45), and (46) together, we obtain for the personal load

$$p_h/n = \left( 1 - \left( a r_a'/\gamma_a \right)^{-1} \gamma_a^{-1} \left( n r_h + \frac{a}{r_a} \frac{r_h}{\gamma_h} \right) \right)$$

This is our most important result. As the first factor reveals, “smartification”, i.e. increasing $a r_a'/\gamma_a$ enhances the personal load and may even lead to instability. Because of the composition of $a r_a'/\gamma_a$, this conclusion holds for both many small AI devices and for few large computer centers. The first term in the second bracket in (47) is proportional to the number $n$ of citizens and describes an increase of personal load.
proportional to the size of the population. Note, however, that we consider the case $n r_h \ll a r_a$, i.e. strong smartification. The last term in the second bracket represents the cooperation of automata and humans. Since we don’t ascribe “creative” power to the automata, $g_a$ depends solely on the import of goods, or external ideas. If the import $g_{hi}, g_{ai}$ as well as personal initiative $g_{he}$ tend to zero, a dying city will result.

### 14.4.1 The Information Crisis

The basic time-dependent equations read.

\begin{align}
\frac{dp_h}{dt} &= n s r_h - \gamma_h p_h \\
\frac{dp_a}{dt} &= a s r_a - \gamma_a p_a \\
\frac{ds}{dt} &= n g_h + a g_a + n r_h' p_h + a r_a' p_a - \Gamma s \\
\end{align}

where

\begin{equation}
\Gamma = \tilde{r}_h n + \tilde{r}_a a + \gamma_e
\end{equation}

To study stability, we consider the homogeneous eqs., i.e. $g_h = g_a = 0$, and make the hypothesis

\begin{equation}
\phi = e^{\lambda t} p_{h0}, \quad p_a = e^{\lambda t} p_{a0}, \quad s = e^{\lambda t} s_0
\end{equation}

Inserting (52) into (48)–(50) leads to the eigenvalue equation.

\begin{equation}
(\lambda + \Gamma)(\lambda + \gamma_h)(\lambda + \gamma_a) - nr_h'(\lambda + \gamma_a) - ar_a'(\lambda + \gamma_h) = 0
\end{equation}

For our purpose it suffices to consider the case where the automata are dominant.

\begin{equation}
a^2 r_a' r_a >> n^2 r_h' r_h
\end{equation}

Then (53) can be reduced to $\lambda = -\gamma_h$ or

\begin{equation}
(\lambda + \Gamma)(\lambda + \gamma_a) - a^2 r_a' r_a = 0
\end{equation}

The solution to (55) reads

\begin{equation}
\lambda_{+,-} = \frac{\Gamma \gamma_a}{2} \pm \frac{1}{2} ((\Gamma - \gamma_a)^2 + 4a^2 r_a' r_a)^{1/2}
\end{equation}

Instability leading to exponential growth occurs if $\lambda_+ > 0$. At the instability, $\lambda_+ = 0$, we find

\begin{equation}
(\gamma_a - a^2 r_a' r_a = 0) \quad (\Gamma \approx \tilde{r}_a a)
\end{equation}

which under the same approximations as above, leads to the previous instability condition

\begin{equation}
1 - \frac{ar_a'}{\gamma_a} = 0
\end{equation}

The exponential increase of SHI will lead to a communication breakdown so that this instability must be avoided. This can be achieved by technical innovations lowering the production rate of SHI e.g. by reducing the transformation rate $r_a'$ by many little improvements or a global breakthrough in AI. A “typical” approach will be increasing the costs of SHI—use (including taxation).
14.5 Final Notes

We conclude this chapter with some notes on urban planning and design in smart cities: As we show in Chap. 15 that follows, the common view is to see urban planning and design as an external intervention in an otherwise spontaneous self-organized urban process. From this perspective, smart cities with their IOT (internet of things), equipped with sensors covering the whole city, data mining techniques that enable to dig into, and exploit, big data, provide urban planning and design stronger tools than ever to plan and design cities. Some would say, to transform the current self-organized, somewhat chaotic, cities into centrally organized cities. And what about the citizens? The answer is that part of the smart city machinery will be able to authentically identify and represent the citizens’ views about the various plans and designs suggested by the professional planners/designers and implemented by the urban planning and design authorities. This approach, as can be seen, assumes a fundamental distinction between the professional planners and designers and the “planned” citizens of the city. This is the common view, as noted, and big companies (e.g. IBM) see here a potential future market. As we elaborate in Chap. 15, our view is different: The lesson from the study of cities as self organizing systems is that every urban agent is a planner at a certain scale and that in many cases, due to nonlinearities, the plan and design of a single person might be more dominant and influential than that of a whole team of professional planners. Examples are the stories of lofts, balconies etc. (cf. Chaps. 4 and 10 above). This view is further supported by cognitive science findings regarding humans’ cognitive chronestetic capabilities for mental time travel and the implied phenomena of cognitive planning and prospective memory (cf. Chap. 15; Portugali 2016a). From this perspective, urban dynamics is seen as on-going self-organized and organizing interaction between the city’s many agents/planners each with its specific local-, mezzo- or global-scale plan. The challenge of smart cities with their IOT would be to develop means to foster this process. In fact, Alexander’s et al. (1977) Pattern Language and the Self-Planned City (Portugali 2011, Chap. 16) are steps toward this aim. There is an additional thought in particular brought forward by Haken (unpublished). The ongoing development and use of AI/IT leads us to reconsider problems in mathematical terms, because quite clearly AI is based on mathematics. According to mathematics there are several classes of problems.

1. Under given conditions, a problem (e.g. in decision making) cannot be solved at all. This is not a purely academic issue, but may have consequences when AI is applied to real life problems (possibly even to traffic steering). Thus we must not expect miracles from AI.

2. In many cases a problem possesses several solutions (cf. Chaps. 5 and 6).
   In sociological context this may lead to a “conflict” situation. Two simple examples may illustrate the case:
   
   traffic
   
   a. left hand drive or
Both regulations are possible, but exclude each other. This conflict can be solved only collectively via government decisions or direct votes.

name giving to married people

(a) regulated by state law
(b) left to couples

In this case also, the “conflict” is solved collectively. This example may seem far fetched, but in fact, conflict situations are ubiquitous in cities and can hardly be solved by automata.

(3) In a number of cases, there exists a unique solution. In such a case, it doesn’t matter, whether the solution is found by humans or automata.

(4) In multi-component/multi-agent/complex systems the processes are of a mixed deterministic/stochastic nature. This requires the study of scenarios (realizations) by a combination of human imagination and insights (see above) and computing power.

A city may be considered as laboratory for innovations for a better quality of life (cf. e.g. Batty et al. 2012) in which the decisions relevant to human welfare must be left to the citizens. In this chapter, aside from some general remarks, we focussed our discussion on the role of AI and information dynamics in cities. We believe that innovations by AI will play an ever increasing role, especially when dealing with the “information crises”.

As the name indicates, AI directs attention to the role of artifacts, the production of which forms one of the basic capabilities of humans. That is, the production of objects that in one way or the other replace the natural capabilities of humans by artificial ones. Thus, some of the early stone tools (e.g. flint knives) replaced the natural human teeth and fingernails as cutting devices. As noted in the introduction, the emergence of cities some 5500 years ago was associated with the invention of writing—among the “smartest” inventions of society—which has partly replaced human memory: A person or society can write their story or thoughts on a stone (or papyrus or tablet or paper or computer) and need not keep it in memory. Already in antiquity this situation entailed a dilemma about the relations between the artifact and the natural human capability. In Plato there is an interesting dialogue between Socrates and Phaedrus in which Socrates expresses his concern about writing:

In fact, it will introduce forgetfulness into the soul of those who learn it: they will not practice using their memory because they will put their trust in writing, which is external and depends on signs that belong to others, instead of trying to remember from the inside, completely on their own. You have not discovered a portion for remembering, but for reminding; you provide your students with the appearance of wisdom, not with its reality. Your invention will enable them to hear many things without being properly taught, and they will imagine that they have come to know much while for the most part they will know nothing. And they will be difficult to get along with, since they will merely appear to be wise instead of really being so.” (Plato. c. 399–347 BCE. “Phaedrus.” pp. 551–552 in Complete Works, edited by J. M. Cooper. Indianapolis IN: Hackett.)
This concern about innovative artifacts accompanies society for many years and is relevant today with the smart artifacts and cities. Looking back at history we can see that writing was not associated with the deterioration of memory: Rather it enabled the externalization and thus the extension of memory—a new form of division of labor between the artificial and natural memory (see SIRN in this respect). As in division of labor in general, so in the case of writing, the challenge was to find a steady state that maximizes the relative advantage of the human memory and that of the artificial memory. The same applies here: the challenge facing smart cities is to identify a steady state that maximizes the relative advantage of the human sensorium and intelligence, and that of the artificial ones.

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