Support Services for the Management and Utilization of Monitoring and Assessment of the MAFEIP Tool

Cost-effectiveness analysis of Smart City interventions

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1. Introduction on the analytical model of decision-making for Smart Cities

The ongoing rapid urbanisation of city regions urges governments to address urban challenges, whereby digitalization is one important element. Despite the widespread existence of Smart Cities across Europe and other continents, little research has been conducted regarding the evaluation of Smart City interventions and the measurement of outcomes of embedded smart technologies for cities and citizens (European Parliament, 2014). In this context, the present case study describes the potential benefits of using the MAFEIP (Monitoring and Assessment Framework for the European Innovation Partnership) tool to evaluate Smart City[1] projects and interventions, by using a cost-effectiveness analysis that has been used extensively in the health economy sector. The MAFEIP-tool is originally developed to assess the impact and cost-effectiveness of digital health interventions, but is highly promising to be used for different digital interventions as well.

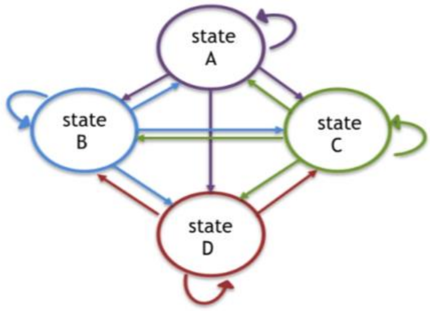
The purpose of the MAFEIP-tool is to estimate the outcomes of a large variety of social and technological innovations, by providing an early assessment of the likelihood that interventions will achieve the anticipated impact. In addition, MAFEIP also helps to identify what drives interventions' effectiveness or efficiency in order to guide further design, development or evaluation. MAFEIP therefore represents a clear support to the decision-making process, also for Smart City projects and interventions.

The MAFEIP tool rests on the principles of Markov's model, which is an analytical decision-making model developed for health economics (Bai, Wu, & Chen, 2015; Giuliani, Galelli, & Soncini-Sessa, 2014; Lewis, 2013; Siebert et al., 2012; Sonnenberg & Beck, 1993). Its main objective is to provide support in the decision-making process, including an *ex ante* analysis before a concrete intervention is implemented. The Markov's model is able to tackle uncertainty on the real effects and costs, and its flexibility allows for the analysis of a large and heterogenous range of interventions. The model uses the best evidence available from multiple sources, such as administration records, official data bases, *ad-hoc* information collected for projects' evaluation or results from evaluations in similar interventions.

Markov's models are based on the definition of a specific number of states (see a four-state example on Figure 1), to which certain costs and effects are defined. These effects can be measured with different indicators depending on the intervention and the objective pursued. One of the key points of this particular model is that it measures the "transition", meaning that it calculates the probability of "population" (which could be defined as citizens, houses, neighbourhoods, sensors, buses, etc.) moving from one state to another one. The model can also take into account the duration of the cycles, by introducing the frequency of these transitions (e.g. monthly, annual, etc.), as well as the total number of cycles of the simulation, that is, for instance, if one wants to conduct an evaluation in five, ten or twenty years.

[1] A systematic review on how to measure the impact of Smart Cities was conducted on: Lupiáñez, F. (2017). Ciudades Inteligentes: Evaluación social de proyectos de Smart Cities. Montevideo: Centro de Estudios de Telecomunicaciones.

Figure 1. Four states of Markov's model



Source: Open Evidence

Costs, effects and probabilities of transition constitute the main parameters of the model and they must be specified both with and without the implementation of the evaluated intervention (actual situation in case of an evaluation *ex ante*, counterfactual, etc.). Based on these, the simulation compares both situations[2] and presents as a main result the incremental cost-effectiveness (ICE). It is calculated for a specific period of time, keeping in mind that the probability of being in each state and all the respective costs and effects. For example, if in period 0 we are in "A" scenario, and we assumed that all population is in the same situation, the associated cost for this period would be C_A and the effect E_A. If the odds of reaching states B, C and D in period 1 are respectively: 0.4, 0.2 and 0.1 (and 0.3 of remain on state A), the cost value of period 1 would be:

$$C_1 = (0.3C_A + 0.4C_B + 0.2C_C + 0.1C_D)$$

And the effect value:

$$E_1 = (0.3E_A + 0.4E_B + 0.2E_C + 0.1E_D)$$

For each period, these values are calculated and included in the evaluation, and they are compared between *non-intervention* and *intervention* situations. Subtracting *non-intervention* costs and effects from *intervention* values, we obtain the **incremental cost and effects (ICE)**. The ICE is the ratio of these two and indicates the cost of getting one effect unit; for example, the avoidable death cost or reduction of a CO_2 ton emission. ICE provides information regarding the suitability of implementing a concrete intervention. The visualization of the ICE can be seen in Figure 2 and Figure 3.

[2] It is also possible to use for more than two alternatives.

Figure 2. Cost-effectiveness table

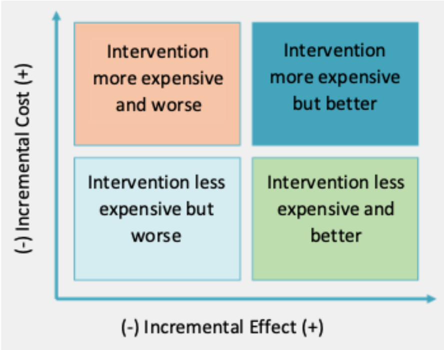
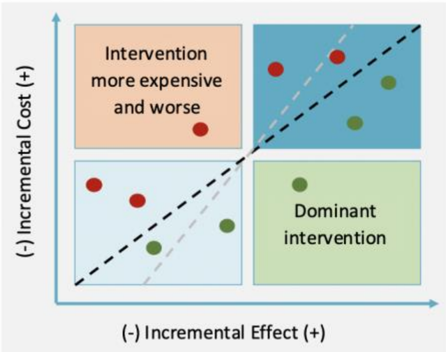


Figure 3. Cost effectiveness table and ICE



The ICE might be in four quadrants depending on cost and effect differences between *intervention* and *non-intervention*. On the top left quadrant, intervention is dominant, it is more expensive and less effective than the alternative one, and therefore, it should not be implemented. On the other hand, if the ICE falls within the bottom left quadrant, the intervention dominates, and it must be applied as it is cheaper and more effective than the initial situation. In terms of the other two quadrants, the decision is less clear. Within the top right quadrant, the intervention is more effective but also more expensive. Regarding the bottom left quadrant, the intervention is cheaper, but less effective. In these two cases, the decision is determined by willingness to pay (WTP), therefore, a project should be implemented if the ICE is lower than the WTP (discontinue lines).

An intervention should be accepted when ICE<WTP, which are shown as the green points in Figure 3. However, an intervention would not be accepted by the ICEs defined by the red points. If WTP was bigger, the line would be more steep (grey line). In that case, if an *intervention* was more effective than a *non-intervention* (top right quadrant), it would be more likely for the ICE point to be placed below the WTP line.

2. Example of a case study using MAFEIP

The next paragraphs describe the procedure to apply the model through a hypothetical intervention: *install sensors in the city to improve public services delivered by buses.* The first step of the evaluation is to **define the intervention and its objectives.** In this case, the intervention purpose would be defined as follows:

Improve public transport organization with sensors that measure traffic, the number of users on each zone, etc. to increment its use and with the final purpose of decreasing pollution levels.

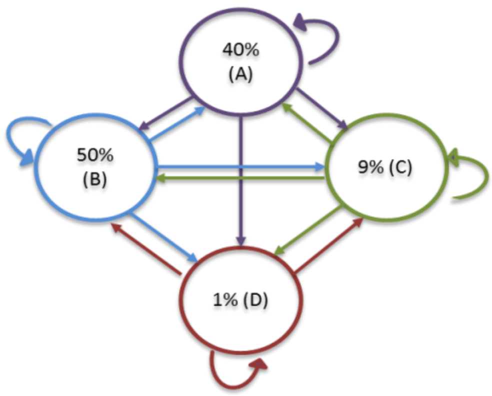
Related to this, it is useful to conduct a **context analysis**. This analysis describes, the different actors involved in the intervention, the main beneficiaries, the elements that can influence its development[3], the time horizon, the inputs that are being used, and the expected impacts. Furthermore, it also describes the situation in which the intervention will (or will not) be implemented because of its (cost-)effectiveness. It is important that this phase counts with the participation of all the main stakeholders in the subject matter.

Next phase consists in **defining the Markov Model states.** Those are defined based on the result of the main variable (outcome), in this case pollution (P) which could be measured with sensors. A hypothetical definition of the states could be:

- State A: Extremely high pollution level (P=40)[4]
- State B: Slightly high pollution level (P=30)
- State C: Medium pollution level (P=20)
- State D: Low pollution level (P=10)

The next step is to define the **initial distribution** of the population across the different states. In this case, the units are the neighbourhoods where it is possible to measure the pollution level. We imagine that 40% are based on State A, 50% on State B, 9% on State C, and just 1% on State D.

Figure 4. Initial distribution of the population in four states



Source: Open Evidence

Once the initial distribution has been completed, it is necessary to **define the transition probabilities** between states, for the *non-intervention* and *intervention* situations. This is the probability that after a certain period (for example, one year), neighbourhoods move from one pollution level, to another. In terms of *ex post* evaluations, transition probabilities are calculated

[3] These can be very diverse: stakeholder behaviour, economic cycle, political context, capacity of the organization to implement the intervention, etc.
[4] "C" shows pollution levels.

based on observed data. For *ex ante* evaluations, the probability of transition of the *intervention* can be based on studies of similar projects, while probability of transition *non-intervention* can be based projections or actual trends. The following tables show a hypothetical situation; if there were 50 neighbourhoods with a slightly high pollution level (state B) and it was estimated that in a year (with no actions taken) 30 of them would increase their pollution's level from slightly high to extremely high (state A), the probability of change from state B to state A in a *non-intervention* scenario would be 0.6. If it was estimated that 5 of those neighbourhoods would move to a medium pollution level, probability of change from B to C would be 0.1. Finally, if it was expected that 15 neighbourhoods would continue with the same pollution level, probability of staying at the same state B would be 0.3 (Table 1). It is necessary to keep in mind that the sum of all the probabilities located in the same row will always be one.

Implementing an intervention to promote public transportation, with the final goal of decreasing the pollution level, could influence the probabilities of transition. For example, out of the 50 neighbourhoods with slightly high pollution level, one could estimate that after a year of intervention, only 5 would increase their pollution level to extremely high, 15 would remain still, 20 would decrease their pollution level to medium, and 10 could achieve lower pollution level. In this case, probabilities of transition into A, C and D states would be 0.1, 0.4 and 0.2 respectively, and 0.3 would be the probability of staying still on the same state B (Table 2). Therefore, intervention would increase the probabilities of transition into less polluted states. Same logic would be applied for neighbourhoods which initially were in the other pollution states (A,C and D).

Table 1. Probabilities of transition between *non-intervention* states.

Non Intervention	Transition a			
Initial state	State A	State B	State C	State D
State A	0,9	0,1	0	0
State B	0,6	0,3	0,1	0
State C	0,2	0,4	0,4	0
State D	0	0	0,2	0,8

Table 2. Probabilities of transition between intervention states.

Intervention	Transition a			
Initial State	State A	State B	State C	State D
State A	0,4	0,3	0,2	0,1
State B	0,1	0,3	0,4	0,2
State C	0,1	0,2	0,3	0,4
State D	0	0,1	0,3	0,6

Next, it is necessary to **assign costs and effects to every state**, both for *non-intervention* and *intervention* situations. In order to do this, **implementation costs** of the project (single costs) such as infrastructure (smart streetlights cost, electric charging stations costs, etc.), staff in charge of the installation, adaption and training costs, as well as bureaucratic costs must be quantified. In addition, necessary **periodic costs** must be calculated to ensure the proper function of the service (such as personnel in charge of providing the service, technical support staff, energy, Internet, management costs, etc.). On the other hand, in order to make the comparison possible, it is necessary to calculate the service costs applicable to that moment in time. Besides costs related directly with service provision, it is also useful to keep in mind any **indirect costs**. Sanitary costs of breathing illness due to pollution would be an example of this case.

Table 3 shows some input costs related to the intervention, while Table 4 shows a hypothetical sum of those elements. Besides that, Table 5 presents some possible indirect costs, which would depend on the level of pollution and which, therefore, are linked to each state. On the example, they are equal in both *intervention* and *non-intervention*, but they could differ in other situations. In that case, there would be the same number of sick people in state A in the case of *intervention* or *non-intervention*. However, the total number of sick people (and costs related to them) would be lower in the intervention scenario because there are more chances to transit to states less polluted, with less associated costs. Moreover, it is necessary to define correctly the unit that one uses to measure costs. In this case, all costs are homogenized per neighbourhood (unit for this example) and per year[5].

Table 3. Intervention Costs. Inputs

	Single Costs	Periodic costs
Non-intervention		Petrol cost
		Bus drivers salary
Intervention	Sensors cost	Petrol cost
	Sensors cost installation	Bus drivers cost
	Training cost for drivers to adapt into new system	Personnel cost who monitorize it

Table 4. Intervention costs. Values

	Single costs (per neighbourhood)	Periodic costs (per neighbourhood and year)
Non-intervention	0	30 MU
Intervention	500 MU[6]	20 MU

[5] Depending on the evaluated intervention, the period could change.

[6] MU: Monetary Units.

Table 5. Indirect costs (per neighbourhood and year)

	State A	State B	State C	State D
Non-intervention	30 MU	25 MU	20 MU	15 MU
Intervention	30 MU	25 MU	20 MU	15 MU

Effects include direct results (related to the program) and indirect results (caused by attitudes and behavioural changes of the affected actors, effects above another sectorial areas of the city, etc.) They can be measured by monetary value, number of avoidable deaths, tons per person, etc. For the inclusion of more than one effect, the measures must be transformed into comparable units, for instance, applying percentages to define priority (environmental effects, effects that benefit the most vulnerable sectors, etc.). Regarding the example, the effects reflect how useful an intervention is to society, depending on the pollution level. It was assumed that less pollution was more useful, as it increases the quality of life, and that it was equal to (100-C)/100. Consequently, costs and effects associated to each state would be:

Table 6. Intervention and non-intervention costs and effects per state

	Intervention		Non-Intervention	
	Costs[7]	Effects	Costs	Effects
State A	500 MU +50 MU/year	0,6	60 MU/year	0,6
State B	500 MU +45 MU/year	0,7	55 MU/year	0,7
State C	500 MU +40 MU/year	0,8	50 MU/year	0,8
State D	500 MU +35 MU/year	0,9	45 MU/year	0,9

We can see that the *intervention* is more expensive because of the initial investment. Nevertheless, if we look into the upcoming years, the difference between the *non-intervention* would be reduced because periodic costs would be smaller. At the same time, if the *intervention* succeeded in moving to states with less pollution, costs would also decrease, since states with less pollution have lower associated costs. Figure 5 presents the costs evolution in both situations (intervention and non-intervention) for a 5-year period, where the *intervention* is more expensive than the *non-intervention,* but the difference between them is reduced. This can be seen on the incremental cost line. These results would change if intervention costs were lower. Figure 6 shows what would happen if initial investment costs were 50MU instead of 500MU. In that case, the intervention would initially be more expensive, but it would bring monetary savings afterwards.

[7] This is the sum of the single costs of the intervention, the periodic costs of the intervention, and the indirect costs.

Figure 5. Cost evolution (1)

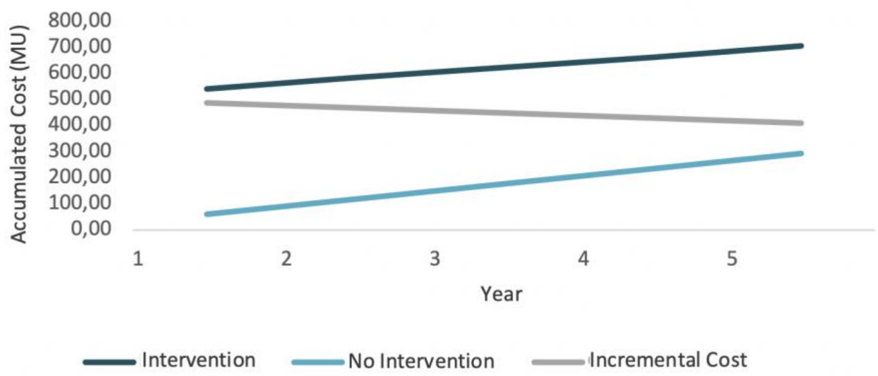
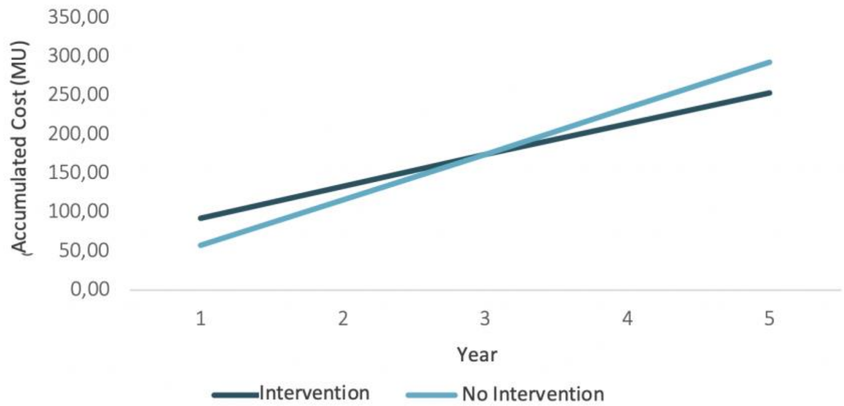
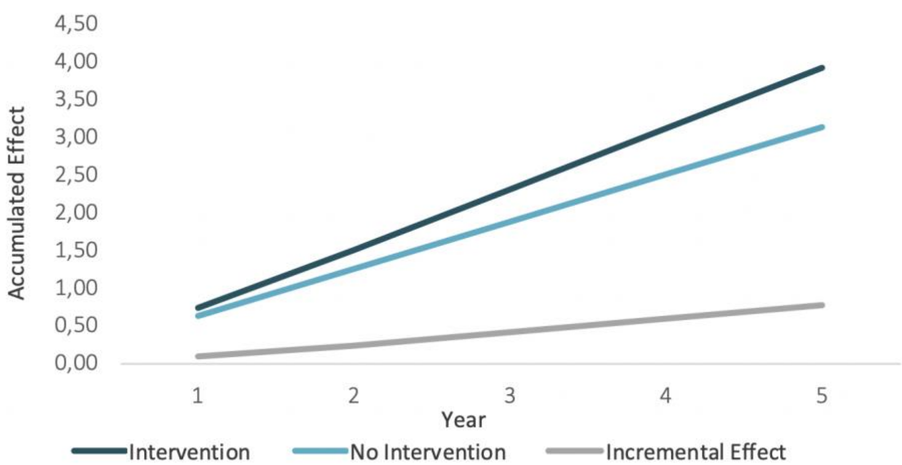


Figure 6. Costs evolution (2)



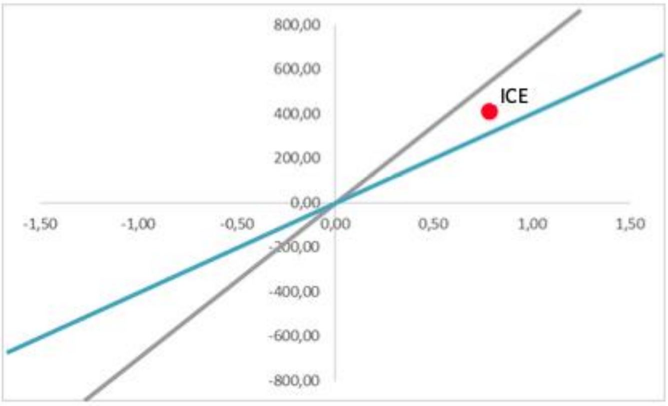
The other key results of the model are the effects derived from intervention, in this case the "usefulness" linked to the pollution level. Figure 7 shows how accumulative *intervention* effects increase faster than *non-intervention* effects (because there are more neighbourhoods transiting to lower pollution levels) and, consequently, the incremental effect is positive and it increases.

Figure 7. Incremental effects



The final result of the evaluation is given by the ICE, which informs the decision making. Whether the program is implemented or not will depend on where the point is located. Figure 8 gives an example of a scenario where the necessary initial intervention investment is 500MU. The horizontal axis represents the incremental effect and the vertical axis represents the incremental cost. The ICE is located on the top right quadrant. Therefore, the willingness to pay for reduction of the level of pollution will be the key to decide if the intervention will be implemented or not. If the willingness to pay is 700MU per usefulness unit (grey line), the intervention would be acceptable because the ICE would be below the threshold. However, if the willingness to pay is 400MU (blue line), the intervention should not be implemented . Therefore, in this scenario the decision would depend on the willingness to pay of the administration in charge of developing the project, which may depend on the available budget, the priority attributed to the impacts pursued by the intervention, etc. Willingness to pay also depends on the citizens or private organizations who will pay for the intervention in a direct or indirect way (through taxes). It should be noted that this willingness to pay is not static and the participation of the main stakeholders may be needed to define the limits in which an intervention would be considered acceptable.

Figure 8. Cost-Effectiveness plan (Scenario 1)



The simulation for Scenario 1 has been conducted under concrete parameters. However, these are just estimations and they may deviate from reality. That is why the model can be run multiple times, demonstrating how results vary when certain parameters are updated. As seen previously, one change in the investment costs may modify the result of the accumulative costs. For example, for Scenario 2 the ICE would be in the bottom right quadrant, meaning the intervention is dominant. That means that it would be cheaper and more efficient than the current option and, therefore, it would be positive to implement it, regardless of willingness to pay (Figure 9). On the other hand, Figure 10 brings a more pessimistic scenario in which the intervention would not be more effective than the current situation and, therefore, the final decision should be to not implement it. The different results would form the set of possible scenarios that could be reached by implementing a certain intervention, which would provide key information to the authorities in charge of making decisions.

Figure 9. Cost-Effectiveness plan (Scenario 2)

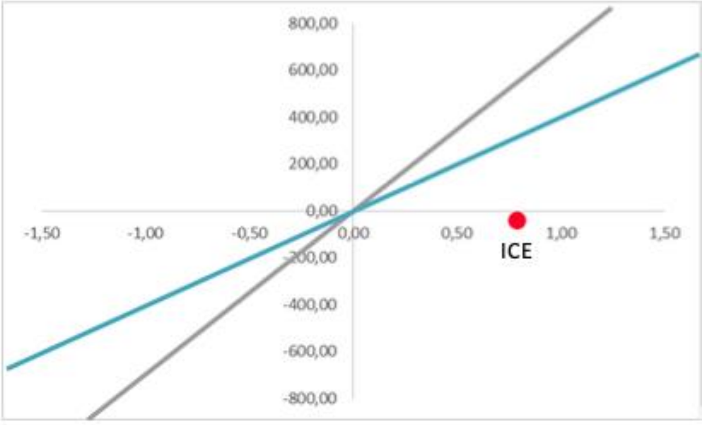
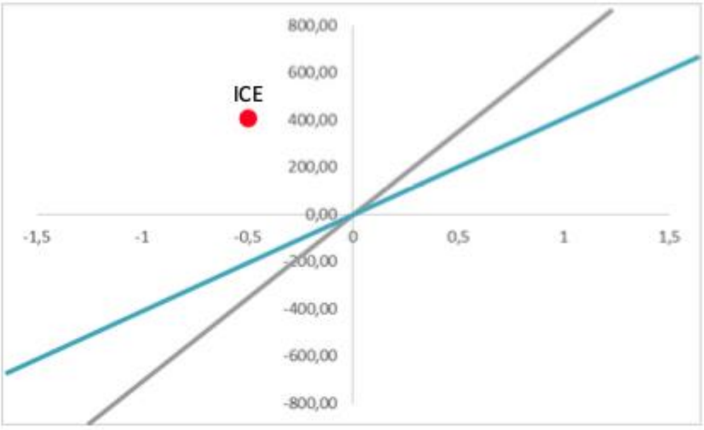


Figure 10. Cost-Effectiveness plan (Scenario 3)



3. Conclusions

Due to the exponential growth of projects and other initiatives to develop and establish Smart Cities, there is a clear need for a reliable and valid methodology to evaluate these initiatives. However, searches carried out have not identified any evaluation framework that is currently addressing this need. As we have shown in the present report, the MAFEIP-tool is highly promising to support evidence-based decision making in the development and uptake of smart city interventions and technologies. MAFEIP goes beyond simple measurement with indicators such as those that we can find on many Smart Cities studies, to inform on the effects produced directly by an intervention and the expected impacts (*ex ante* evaluation). The MAFEIP-tool compares the costs and the efforts invested with the results to examine the profitability and the feasibility, giving Smart Cities interventions and technologies a chance to improve their efficiency and effectivity and be able to improve decision making in this field.

Evaluation plays a fundamental role in the development of projects, since it is what allows decision-makers to identify programs that obtain the expected results. Additionally, the *ex ante* evaluation analyzes the expected results of one or more interventions before their application, in order to decide whether their implementation is recommended. For each intervention, MAFEIP analyses how the costs are related to its effects, taking into account the willingness to pay. The results can be positive or negative, of greater or lesser degree, and with a possible differential effect depending on the actors. MAFEIP allows the choice between alternatives that are normally exclusive due to budgetary restrictions, and cannot be applied simultaneously. Thus, it is essential to make use of the evaluation before, during and at the end of each public program or intervention with a public impact, like all those that fall within the framework of Smart Cities.

4. References

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