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AI and Simulation for Performance Assessment in Collaborative Business Ecosystems

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Abstract. Artificial Intelligence advances have enabled smarter systems, which in the business world, particularly in Collaborative Business Ecosystems, can lead to more streamlined, effective, and sustainable processes. Moreover, the use of well-defined performance indicators to assess the organisations' collaboration level can influence their behaviour, expecting to improve their performance and that of the ecosystem. This paper presents a case study using a simulation and agent-based model to represent the organisations' behaviour. True data gathered from three IT industry organisations running in the same business ecosystem allowed to shape the model with three classes of agents with different collaboration willingness levels. As such, some scenarios are simulated and discussed, considering a CBE populated with a given combination of organisations and a variation of the weighted adopted performance indicators.

Keywords: Collaborative Networks, Business Ecosystem, Performance Indicators, Simulation, Agent-Based Modelling, Reinforcement Learning.

1 Introduction

Artificial Intelligence (AI) progress have enabled smarter systems, which in the business world, particularly in Collaborative Business Ecosystems (CBEs), can streamline collaborative processes among organisations, promoting its sustainability and resilience [1]. We adopted the name CBE [2] according to Moore's view [3], who was the first to introduce the term Business Ecosystem inspired by biological ecosystems, and according to Camarinha-Matos and Afsarmanesh's taxonomy of a Collaborative Network (CN) [4, 5], to highlight the collaboration aspect of our view of a business ecosystem.

An essential facet in this context is evaluating the collaboration performance between organisations in an ecosystem to identify potential earnings. On the one hand, many studies can be found in the literature at the network level, supporting broad theories on inter-organisational networks, many of them highlighting the capabilities that come with it [6]. However, just a few studies on business networks can be found [7] and more particularly on evaluating their collaboration, despite some performance

assessment attempts. Some examples of such attempts include: (i) A proposal of indicators of collaboration and for relationship and assets analysis in CNs [8, 9]; (ii) Suggestions of using balanced scorecards in CNs [10, 11] and supply chain management [12, 13, 14]; (iii) various methods and metrics to measure the performance of supply chain collaboration [15, 16, 17, 18]; and (iv) Structural analysis of the relationships that link actors in social network analysis as an essential input for the design of performance indicators [19].

The identification of this need motivated our work, driven by the following research question:

What can be a suitable approach to assess collaboration performance and promote collaboration sustainability in a collaborative business ecosystem?

Collaboration is a key element of sustainability, deriving its benefits from differences in perspectives, knowledge and approaches. It also solves problems while offering benefits to all the participants in the process. [20]. Some frequent benefits include optimising human and financial capital, access to the markets and knowledge, the emergence of creativity by utilising diversity of participants' backgrounds, more efficient use of resources, and shorter time to reach objectives [20]. As such, we argue that promoting collaboration in a CBE is an incentive towards its sustainability.

This paper presents a case study using a CBE simulation model, previously proposed in [22], populated with agents representing the organisations whose behaviour is modelled using true data gathered during the year 2019 from companies running in the same ecosystem in the IT industry. The organisations have different profiles classified into classes of collaboration willingness that characterize their collaborative behaviour and their response when assessed by a Performance Assessment framework proposed in [23]. Similar to individuals, when organisations know how they are measured, it is expected that they adjust their behaviour in order to increase their evaluation results. Thus, this study aims to show that the organisations' collaboration performance and that of the ecosystem can be improved by the CBE Manager, using the Influence Mechanism proposed in [24].

The remaining sections are organised as follows: section two presents the relationship with innovation in Artificial Intelligence systems; section three presents the simulation model, describes the true data used to configure the agents' behaviour, briefly explains the performance assessment and the influence mechanism, details the internal behaviour of an agent and finally presents and discusses the simulation results of different scenarios; the last section contains a summary of the study, refers the ongoing work and identifies future work.

2 Relationship with Innovation in Artificial Intelligence Systems

Facing today's challenges and supporting the digital transition encourages organizations to apply Artificial Intelligence (AI) to their business areas to improve sustainability and quality of life. Efforts have been made in AI to build rational agents capable of perceiving the world and taking actions to advance specified goals [25]. In

our case, a CBE can be modelled with reasoning agents that simulate companies' behaviour as a mean to understand the pattern of decisions that produce value.

This work presents a CBE simulation model to assess the influence of collaboration among organisations. The CBE is seen as a community of agents that interact, creating relationships to accomplish business opportunities. A particular emphasis is put on modelling the behaviour and reasoning mechanisms of the various agents. The work also focuses on understanding how a chosen set of performance indicators can influence the behaviour of those agents and the global performance of the CBE.

The use of Reinforcement Learning (RL), as illustrated in Fig. 1, a field of AI increasingly applicable to real-life problems [26], can lead to optimized decisions in the CBE. Applied to the performance assessment of a CBE, RL can play a role by training some agents, i.e. some organisations ($O_1, O_2, O_3, \dots, O_n$) in the CBE simulation model, to learn the best collaboration decisions to optimise their performance, and consequently, that of the CBE. This aspect corresponds to a planned extension to the performed work described in this paper.

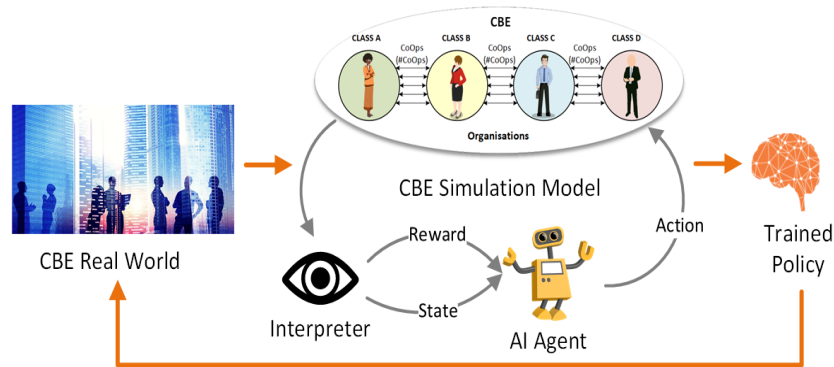


Fig. 1. Reinforcement Learning applied to a CBE simulation model for performance assessment and optimization

3 The Simulation Model

Considering the simulation objectives of this study in evaluating the performance of CBEs, we adopted the Performance Assessment and Adjustment Model (PAAM) [22], illustrated in Fig. 2, which is designed using AnyLogic tools [27]. A CBE model can be represented as a business environment composed of organisations collaborating in response to market opportunities. These collaborations are relationships between the organisations expressed in collaboration opportunities (*CoOps*), represented in the model of Fig. 2 by links, which, in turn, have a weight that corresponds to the number of times the organisations collaborate (*#CoOps*).

Organisations are of different profiles classified into Classes of Collaboration Willingness, which characterize their collaborative behaviour when realizing market opportunities. Each profile is made up of a set of attributes, namely *Contact rate*, *Accept rate*, and *New products rate*, whose decimal values between 0 and 1, expresses a

collaboration intensity factor, i.e., the propensity to collaborate by sending invites to other organisations, the inclination to accept the invitations, and in particular those that are associated to innovation. Table 1 describes a CBE in terms of its structural organisation and collaborative behaviour. It is possible to instantiate the CBE model with any number of organisations of different profiles, characterized by classes of collaboration willingness generically designated by Class A, B, C, ..., Z.

The PAAM of Fig. 2 also includes a Performance Assessment to measure the collaborative behaviour of the CBE by using performance indicators: Contribution Indicator (CI), Prestige Indicator (PI), and Innovation Indicator (II). The CBE Manager can adopt some or all of the indicators with a given weight (w_{CI} , w_{PI} and w_{II}), which acts as an Influencing Mechanism in organisations, hoping to influence a change in their behaviour, since, in the same way as individuals, organisations also adapt to the way they are assessed. The CI influences the organisations' accomplished capacity, PI is more related to reputation, and II influences innovation creativity.

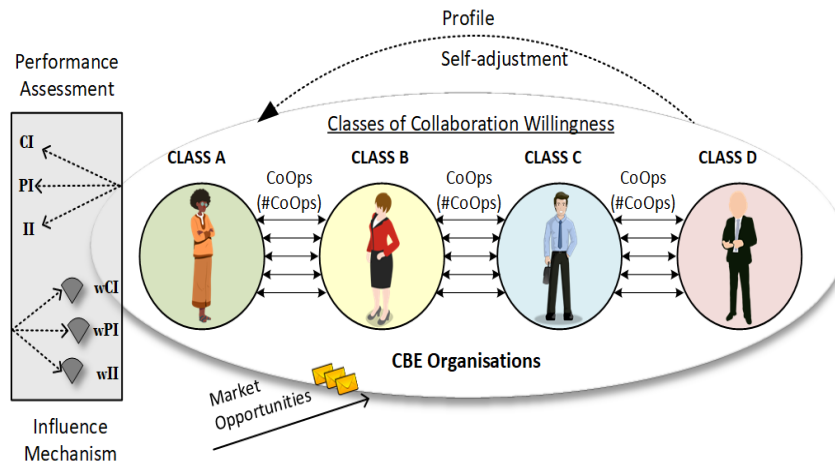


Fig. 2. Conceptual view of the PAAM (Performance Assessment and Adjustment Model) for a CBE

Table 1. A framework to understand and model a CBE.

Model of a CBE		
Description	A CBE is a network of organisations, connected by relationships that mean the market opportunities they share collaborating, called collaboration opportunities, to accomplish business opportunities.	
Structural Organisation	Name	Model
	Collaborative Business Ecosystem (CBE)	Network of nodes
	Organisations (O_n)	Nodes
	Collaboration opportunities (CoOps)	Ties between nodes
	Number of shared CoOps (#CoOps)	Ties' strength
Collaborative Behaviour	Classes of Collaboration Willingness	Profiles of Organisations
	Contact rate [0..1] Willingness to invite other organisations to collaborate.	
	Accept rate [0..1] Readiness to accept invitations from other organisations.	
	New products rate [0..1] Tendency to accept opportunities related to innovation.	

3.1 Characterisation of the Data

An implemented experiment using the PAAM model instantiates five organisations for each of the three classes of collaboration willingness, shown in Fig. 3, according to Table 1, namely Class A, Class B and Class C, which are characterized in Table 2 by radar charts.

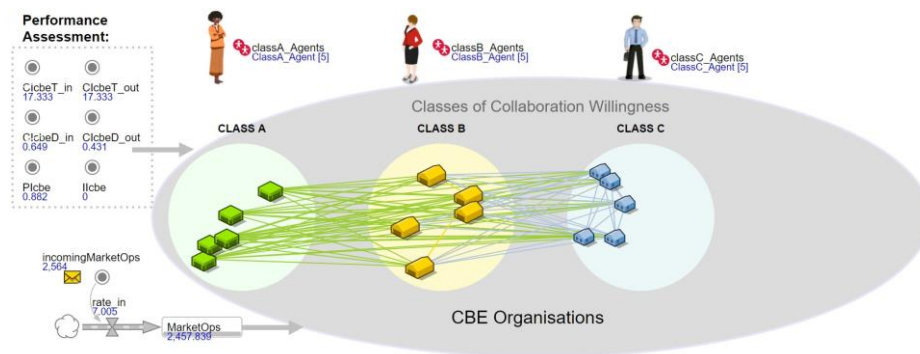
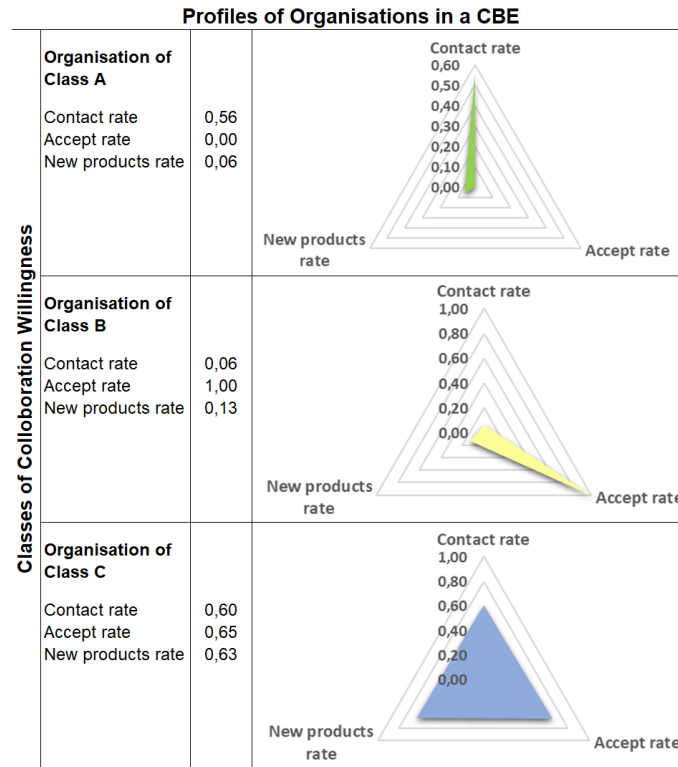


Fig. 3. A view of the PAAM (Performance Assessment and Adjustment Model) for a CBE instantiated with five organisations for each of the three different classes of collaboration willingness

Table 2. Profile of the organisations, instantiated in the CBE, classified in different classes of collaboration willingness (Class A, B, and C).



Each class uses true data collected during 2019 from three organisations operating in the IT sector in the same business ecosystem. As such, it is possible to configure the different organisations' behaviour (the agents in the model) to perform more realistically. These data, consolidated in Table 3, allow estimating the classes of collaboration willingness (*Contact rate*, *Accept rate* and *New products rate*). The data also includes the total number of human resources (expressed in quantity and days/person) and percentage of allocation by main activity (consulting, research & development and inner tasks), the number of market opportunities sent and received, expressed in days/person (min, max and mode, i.e. the typical duration), and the percentage (min and max) of the opportunity involved in the collaboration, i.e. the units to distribute in a collaboration opportunity (*CoOp*).

Table 3. Consolidated real data from the organisations, considered as Class A, B, and C.

	Organisation of Class A	Organisation of Class B	Organisation of Class C
Resources	value	value	value
Total (persons)	62	16	33
Total (days/person)	13640	3520	7260
Consulting	74%	87%	85%
R&D	2%	0%	6%
Inner Tasks	24%	13%	9%
Market Opportunities	min	mode	max
Duration (days/person)	0	20	100
Classes of Co. Willingness	value	value	value
Contact rate	0,56	0,06	0,60
Accept rate	0,00	1,00	0,65
New products rate	0,06	0,13	0,63
Units to Distribute	min max	min max	min max
	4,0% 7,2%	0% 16,7%	0,4% 4,5%

3.2 Performance Assessment and Influence Mechanism

The Performance Assessment for CBEs introduced in [24] and briefly described in Table 4: CI, PI and II, allows to evaluate the collaborative performance of the CBE through the performance indicators adopted by the CBE Manager. These indicators use centrality and density metrics inspired by Social Network Analysis, whose network structures are described as social capital [28]. On the other hand, applied to inter-organisational research, the network structure and strength of the links among organisations influence their behaviour and performance [6]. Moreover, findings suggest that strong links among organisations increase trust, which, in turn, increases benefits and lowers transaction costs [6]. The organisations' high degree centrality is positively related to their performance, and structural holes and closure generate social capital [6]. The exposed performance indicators take these concerns into account: CI measures the value creation in terms of new collaboration opportunities created in the CBE, PI measures how collaboration among organisations spreads, highlighting those that are most influential, and finally, the II measures the new products, services or patents created in collaboration.

Based on each indicator's objective, organisations are expected to react differently, according to their profiles' characteristics, as a response to a set of influence factors, the Influence Mechanism introduced in [24] and summarized in

Table 5. Each indicator has an associated weight (defined by the CBE Manager) to allow a more meaningful influence on the direction that the CBE Manager intends to enhance: the *Contact rate* is related to CI (the more the contacts, the more likely to create *CoOps* in the CBE), the *Accept rate* related to PI (the more the accept of *CoOps*, the more likely to be influent in the CBE), and the *New products rate* related to II. As such, given a factor of influence (FI%), the organisations' class of collaboration willingness is increased by a percentage calculated by formulas FI_{wCb} , FI_{wPI} , and FI_{wII} . Formulas consider an influencing factor ($\pm Fe$) to add a positive or negative exogenous/random influence.

Table 4. Summary of the Performance Indicators to evaluate collaboration in a CBE.

Performance Indicators	
Contribution Indicator of an Organisation (CI_i) and the CBE (CI_{CBE})	
$CI_i \text{ in/out} = \frac{C_D(O_i) \text{ in/out}}{C_D(O^*) \text{ in/out}} = \frac{\sum_j O_{ij} \#CoOp_{ij} \text{ in/out}}{\max \sum_j O_{ij} \#CoOp_{ij} \text{ in/out}}$	Assesses the contribution of organisation O_i in terms of the number of accepted/created (in/out) collaboration opportunities (#CoOp).
$CI_{CBE} \text{ in/out} = \frac{\sum_i [C_D(O^*) \text{ in/out} - C_D(O_i) \text{ in/out}]}{C_D(O^*) \text{ in/out} * (\#O - 1)}$	Assesses the degree to which the most popular/active organisation [max degree centrality $C_D(O^*)$ in/out] exceeds the contribution of the others.
$CI_{CBE}^t = \frac{\sum_i \#CoOp_i}{\#O}$	Ratio of the total number of collaboration opportunities (#CoOp) created/accepted in the CBE by the total number of organisations (#O).
Prestige Indicator of an Organisation (PI_i) and the CBE (PI_{CBE})	
$PI_i = \frac{C_B(O_i)}{C_B(O^*)} = \frac{\sum_k \sum_j O_{kj}(O_i)}{\max \sum_k \sum_j O_{kj}(O_i)}$	Assesses the prominence/influence of organisation O_i in terms of the number of collaboration opportunities (#CoOp).
$PI_{CBE} = \frac{C_B(CBE)}{\max C_B(CBE)} = \frac{\sum_i [C_B(O^*) - C_B(O_i)]}{C_B(O^*) * (\#O - 1)}$	Assesses the degree to which the most prominent/influent organisation [max betweenness centrality $C_D(O^*)$] exceeds the contribution of the others.
Innovation Indicator of an Organisation (II_i) and the CBE (II_{CBE})	
$II_i = \frac{\#NewPd_i}{\#PortPd_i}$	Measures the ratio of the number of new products/services/patentes (NewPd _i) of the organisation O_i by the total portfolio (PortPd _i) created.
$II_{CBE} = \frac{\sum \#NewPd_i}{\sum \#PortPd_i} * r(\#VO, \#NewPd)$	Calculates the ratio of innovation of the organisations in the CBE, weighted by the correlation between the collaboration (participation in Vos) and new products/services/patentes [$r(\#VO, \#NewPd)$].

Note: The values of the indicators are normalised between [0..1].

Table 5. Summary of the Influence Mechanism of the organisations in a CBE.

Influence Mechanism				
Classes of Collaboration Willingness	Related to	Perf. Indicator	Weight	Factor of Influence (FI %)
Contact rate	It is related to activity	CI	wCI	$FI_{wCI} = wCI * \frac{FI}{wCI + wPI + wII} \pm F_e$
Accept rate	It is related to prominence/influence	PI	wPI	$FI_{wPI} = wPI * \frac{FI}{wCI + wPI + wII} \pm F_e$
New products rate	It is related to innovation	II	wII	$FI_{wII} = wII * \frac{FI}{wCI + wPI + wII} \pm F_e$

3.3 Model of the Agents

In the PAAM model, organisations are modelled as agents (ABM) that use statecharts, system dynamics (SD), and distribution functions [27] to simulate their behaviour, as shown in Fig. 4. The statechart is responsible for an agent's state transitions. On the other hand, the SD provides stocks for human resources: *Consulting*, *Research & Development*, and *Inner Tasks*. Finally, when an organisation receives a new *CoOp* (*InviteReceived*) or invites others to collaborate (*InviteToCollaborate*), it uses probabilistic functions parametrized with the classes of collaboration willingness: *Contact rate*, *Accept rate* and *New Products rate*. The resultant formulas (1), (2), (3) use the Bernoulli distribution, where the higher the parameters, the higher the probability of having a positive outcome if resources are available. Formula (4) uses a Triangular distribution to generate the number of business units to give to other organisations when collaborating.

$$\begin{aligned}
 invite_{toCollaborate} &= \text{bernoulli}(\text{contactRate}) & (1) \\
 accept_{collaboration} &= \text{bernoulli}(\text{acceptRate}) & (2) \\
 accept_{collaboration} &= \text{bernoulli}(\text{newProductsRate}) & (3) \\
 businessUnits_{toDistribute} &= \text{triangular}(\text{minUnits}, \text{maxUnits}) & (4)
 \end{aligned}$$

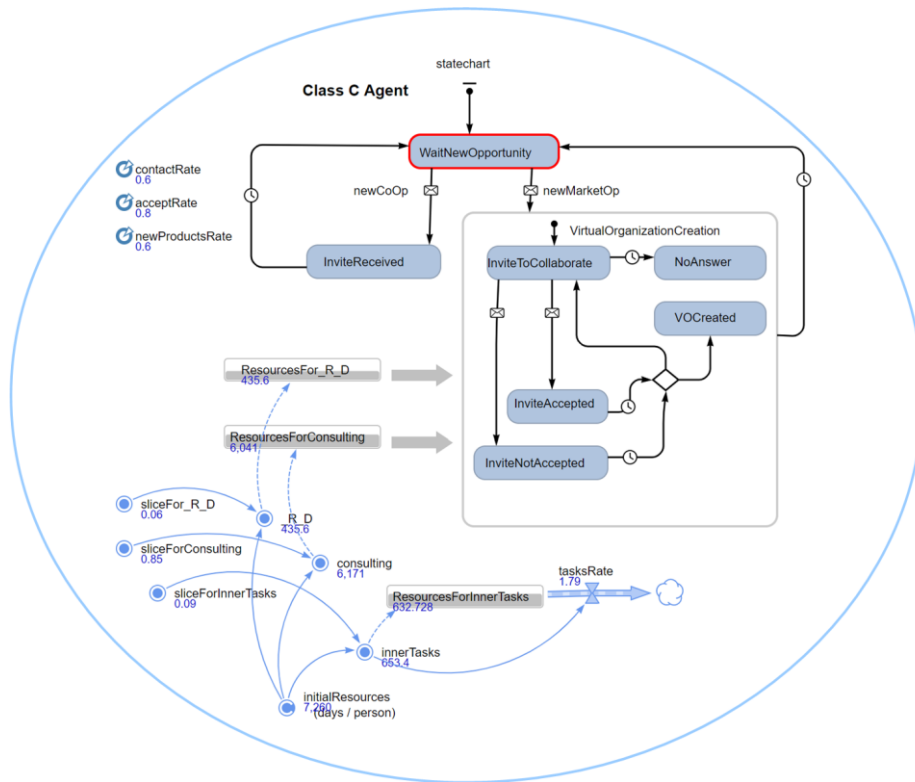


Fig. 4. Zoom in a Class C agent (organisation), showing the detail of its behaviour modelling

The CBE Manager may vary the weights of the adopted performance indicators to

influence the agents' behaviour, resulting in the simulation model, in an increment of the corresponding parameters: *Contact rate*, *Accept rate* and *New products rate*. This influence causes a change in the organisations' behaviour in the desired direction, the same way as individuals, when they know they are measured, their behaviour is adjusted to perform towards that goal.

On the other hand, reinforcement learning in the simulation model can help the CBE Manager understand how to achieve an assessment goal for an individual organisation or the whole ecosystem. The environment (CBE environment in this case) is typically stated in the form of a Markov decision process (MDP) [29], and the AI agents, based on the environment's status, ought to take actions in order to maximise the notion of cumulative reward.

3.4 Simulation Results

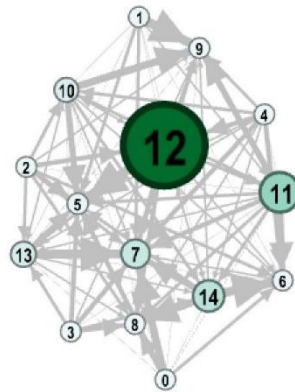
Considering the PAAM model configured with three IT organisations' true data, as shown in Fig. 3, the outcomes can be attained using the Performance Assessment and Influence Mechanism summarized in Table 4 and Table 5. The model ran one year (virtual time) in the simulation environment using Poisson's distribution [27], assuming 2 thousand market opportunities, plus 20% of opportunities with innovation.

This experiment analyses the PI outcome in three scenarios: (A) measures without influence; (B) measures with a $FI=20\%$ and the weights $w_{CI}=2$, $w_{PI}=5$, and $w_{II}=1$; and (C) measures with a $FI=20\%$ and the weights $w_{CI}=5$, $w_{PI}=2$, and $w_{II}=1$.

Analysing the results of the three simulation's scenarios in Table 6 and the graphical representation (Gephi tool [30]) in Fig. 5 and Fig. 6, we can observe that due to the profile of organisations of Class A have an *Accept rate* = 0, the PI indicator that is more related to prominence is equal to zero and remains zero after de influence mechanism. However, we can perceive the organisations' bias in scenario (B) to acquire more prestige due to the influence mechanism. The same trend can also be observed in scenario (C) but not as pronounced given the PI's lower weight. Both scenarios (B) and (C) show an improved CBE as a lower measure of the PI_{CBE} means a more uniform collaboration.

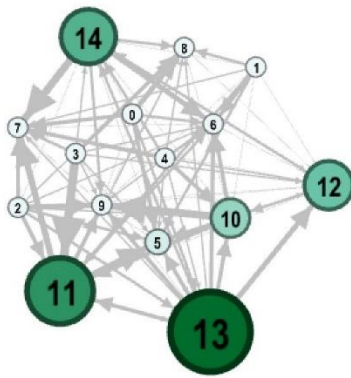
Table 6. Shows PI normalized measures for organisations and the CBE, using three scenarios of simulation: (A) without the influence mechanism; (B) after influenced considering a $wPI = 5$; and (C) after influenced considering a $wPI = 2$.

Profile	O_i	PI Outcomes		
		PI_i (A)	PI_i (B)	PI_i (C)
Organisations of Class A	0	0,00	0,00	0,00
	1	0,00	0,00	0,00
	2	0,00	0,00	0,00
	3	0,00	0,00	0,00
	4	0,00	0,00	0,00
Organisations of Class B	5	0,00	0,08	0,07
	6	0,00	0,00	0,00
	7	0,13	0,00	0,03
	8	0,00	0,00	0,13
	9	0,00	0,00	0,00
Organisations of Class C	10	0,06	0,31	1,00
	11	0,32	0,77	0,67
	12	1,00	0,48	0,49
	13	0,08	1,00	0,90
	14	0,18	0,25	0,72
PI_{CBE}		0,88	0,81	0,73

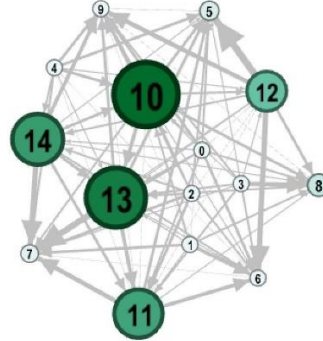


(A) PI measures before the influence.

Fig. 5. Graphical view of PI measures before the CBE's influence; the nodes' size is related to the PI value. i.e., the bigger the nodes, the greater the indicators' values; the connections' strength is weighted by the number of collaboration opportunities in the organisations.



(B) PI measures after the influence.



(C) PI measures after the influence varying the indicators' weights.

Fig. 6. Graphical view of PI measures before the CBE's influence considering (B) $wPI=5$ and (C) $wPI=2$; the nodes' size is related to the PI value. i.e., the bigger the nodes, the greater the indicators' values; connections' strength is weighted by the number of collaboration opportunities in the organisations.

5 Conclusions and Further Work

The simulation results showed that it is possible to configure the PAAM model using real data from organisations to obtain realistic scenarios. The PI indicator's simulation outcomes using the Performance Assessment and Influence Mechanism showed that the CBE collaboration can be measured and influenced by varying the weights of the performance indicators adopted by the CBE Manager. In this way, organisations can be influenced to improve their collaboration performance, thereby improving collaboration sustainability in the CBE, due to the benefits collaboration can bring, as argued in [20].

The ongoing work is related to analysing more comprehensive simulation scenarios, using the same actual data to configure different combinations of organisations' profile and different combinations of the proposed performance indicators.

Future work includes the design of more complete and reasoning agents to model the organisations' behaviour towards more intelligent decisions promoting a more sustainable CBE.

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