# Destabilising Conventions: Characterising the Cost

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***Abstract*—Conventions are often used in multi-agent systems to achieve coordination amongst agents without creating additional system requirements. Encouraging the emergence of robust conventions via fixed strategy agents is one of the main methods of manipulating how conventions emerge. In this paper we demonstrate that fixed strategy agents can also be used to *destabilise* and remove established conventions. We examine the minimum level of intervention required to cause destabilisation, and explore the effect of different pricing mechanisms on the *cost* of interventions. We show that there is an inverse relationship between cost and the number of fixed strategy agents used. Finally, we investigate the effectiveness of placing fixed strategy agents by their cost, for different pricing mechanisms, as a mechanism for causing destabilisation. We show that doing so produces comparable results to placing by known metrics.**

***Keywords*—conventions; cost; destabilisation; emergence; norms; social influence**

## I. Introduction

Coordination is fundamental to multi-agent systems (MAS) and self-organisation as it increases the efficiency of systems. Coordination is required as incompatible actions cause conflicts or incur costs. However, it is often impossible to constrain agents beforehand to ensure coordination. This can be due to lacking knowledge of clashing actions or the inability or unwillingness to dictate behaviour. This is of particular importance in self-* systems without centralised control or where the range of possible actions makes pre-determination infeasible.

Hence, many MAS rely on the emergence of conventions, in the form of expected behaviour adopted by agents, with minimal prior involvement by system designers. As such, conventions allow coordinated actions to emerge through self-organisation. In particular, conventions have been shown to emerge given only agent rationality and the ability to learn from previous interactions. Understanding their emergence and what system characteristics might influence them is an area of active research [1], [2], [3], [4], [5].

Fixed strategy agents, that always choose the same action regardless of others' choices, have been shown to facilitate rapid convention emergence and to influence the adopted action. A small number of such agents, placed suitably, are able to influence a much larger population [2], [4], [6]. However, in realistic domains there is likely to be a cost associated with inserting a fixed strategy agent, or persuading an agent to act in a particular way, and it is desirable to minimise this cost.

It is useful to have the ability to replace existing conventions, as well as to establish new ones. Suboptimal conventions that have emerged, either due to restricted agent knowledge or a temporal quality of optimality, can be replaced with better conventions. Understanding how these changes can be instigated will also allow the design of mechanisms that increase convention robustness.

This paper considers what is required to *destabilise* an established convention. We propose temporarily inserting agents, known as *Intervention Agents* (IAs), with strategies that differ from the established convention to influence a population into discarding the established convention. Using this approach we show that a small proportion of IAs placed at targeted locations in the population for a sufficient length of time can destabilise an established convention, replacing it with another of our choosing. We also establish that the cost of these interventions varies inversely with the number of IAs used and that this effect is replicated across different pricing mechanisms. Finally we examine how the costs associated with agents may be used to inform IA placement. We show that, provided the associated costs are an indication of influence, placing by cost yields results similar to placing by network position metrics.

The remainder of this paper is structured as follows: in Section II we examine the related work on convention emergence and fixed strategy agents. Section III describes the model of convention emergence and metrics for characterising conventions used in this paper. The experimental setting is described in Section IV, and our results are presented in Section V. Finally, our conclusions are presented in Section VI.

## II. Related Work

A *convention* is a socially-accepted rule regarding behaviour. There is no explicit punishment for going against it, nor any implicit benefit in the conventional action over similar actions. The convention members expect others to act in a certain way, and deviation from this increases the likelihood of coordination issues and costs. A convention is "an equilibrium everyone expects in interactions that have more than one equilibrium" [7]. They are able to emerge from local agent interactions [1], [3], [8], [9] and enhance coordination by placing *social constraints* on the actions that agents are likely to choose [10].

The assumptions regarding agent behaviour are only rationality and a (limited) memory of previous interactions. Convention emergence with these assumptions has been the focus of numerous studies [1], [4], [6], [9]. Walker and Wooldridge [9] investigated convention emergence with few assumptions about agents' capabilities. They show global convention emergence is possible based on agents observing others' actions. Building on this, Sen and Airiau [4] explored social learning as a model for emergence, where agents receive a payoff from their interactions to inform their learning (via Q-Learning). They show that convention emergence can occur with no memory of interactions and agents only being able to observe direct interactions. However, their model is limited as agents are not situated within a network topology and can interact with any other agent, and the convention space has only two possible actions. Network topology has been shown to have a significant effect on convention emergence [1], [3], [5], [11]. Recent work has investigated larger action spaces and has shown that this typically slows convergence [2], [6], [12].

Sen and Airiau [4] show that a small number of fixed strategy agents can cause a population to adopt the strategy as a convention over other equally valid choices. This indicates that small numbers of agents can affect much larger populations. Franks *et al.* [2], [13] investigated fixed strategy agents where interactions are constrained by a network topology with a large convention space. They found that topology affects the number of such agents required to increase convergence speed. They also established that *where* such agents are placed is a key factor in how influential they are, with placement by metrics such as degree or eigenvector centrality being significantly more effective than random placement.

Previous work often assumes no restrictions when placing fixed strategy agents into the network. We follow this assumption, but add that such an insertion has an associated *cost*. In real-world domains, inserting fixed strategy agents likely has a cost, and understanding how to minimise this is crucial. In this paper, we investigate the effect of the cost of insertion and its relation to the duration and efficacy of intervention.

Previous investigations of fixed strategy agents typically insert them at the beginning of a simulation. We investigate insertion when a convention has already become established with the aim of causing members of the dominant convention to cease using it. Previous work has shown that destabilisation is possible [14], and in this paper we examine the minimum level of intervention required to cause destabilisation, and explore the effect of different pricing mechanisms and the effectiveness of placing fixed strategy agents by their cost.

## III. Convention Emergence Model

Convention emergence occurs as a result of agents in a population learning the best strategy over time. Each timestep, every agent will choose one of its neighbours to interact with. Both choose an action from the available strategies and receive a payoff that is determined by the combination of actions. In this paper, the interaction and payoff are based on the n-action coordination game, such that agents receive a positive payoff if they select the same action and a negative payoff otherwise. We utilise the n-action coordination game to avoid restricting the number of possible conventions to a binary choice.

Each agent chooses the action that it believes will result in the highest payoff from knowledge of prior interactions. Agents also have the capability to explore the action space, such that with probability $p_{explore}$ agents will choose randomly from the available actions. We adopt the approach of Villatoro *et al.* [5], using a simplified Q-learning algorithm for both partners to update their strategies. Additionally, agents are situated on a network topology that restricts their interactions to their neighbours. We consider small-world and scale-free topologies as these exhibit properties observed in real-world networks. We also examine random topologies as a baseline.

We utilise the convention membership metrics formulated by Marchant *et al.* [14]. These metrics offer ways of measuring when a convention exists as well as how strongly an agent *adheres* to it. Using this, we can state when a convention is *established* as well as measuring the *membership* of the convention. Doing so allows us to monitor the emergence, growth and destabilisation of conventions without having access to agent internals. We are also able to distinguish, by their adherence, between agents who have chosen a strategy at random and those who are members of the convention.

### A. Intervention Agents

As discussed in Section II, in contrast to previous work we examine the effect of introducing fixed strategy agents once a convention has emerged. We call such agents *Intervention Agents* (IAs) and, expanding on the work of Franks *et al.* [2], [13], we introduce IAs as replacements for agents within the primary convention (the convention with the highest membership) with the aim of destabilisation. The length of time these agents are left within the system is varied to explore the level of intervention needed to cause permanent change.

## IV. Experimental Setup

Our experimental setup is based on that used by Marchant *et al.* [14], in which a population of 1000 agents use Q-learning in the 10-action coordination game. The learning and exploration rate are both set to $0.25$. Unless stated otherwise, all simulations are averaged over 30 runs.

An interaction window of $\lambda = 30$ is used for adherence approximation, and actions for which at least one agent has selection probability of $\gamma \geq 0.5$ are considered (potential) conventions. The adherence threshold for an established convention is $\beta = 0.9 \times (1 - (p_{explore}(N-1))/N))$, where $N$ is the number of strategies, $p_{explore}$ is the exploration rate, and $(N-1)/N$ represents the ratio of random choices that are not the convention's strategy.

Interaction topologies were generated using the Java Universal Network/Graph Library. Scale-free topologies were generated using the Barabási-Albert algorithm with 4 initial vertices and 3 edges added from a new node to existing nodes each evolution of the topology [15]. The Kleinberg model was used to generate small-world topologies with a lattice size of $10 \times 100$, clustering exponent $\alpha = 5$ and one long distance connection per node [16].

Convention emergence and stabilisation occurred within 5000 timesteps for all topologies. IAs were then introduced, replacing nodes within the primary convention according to the placement strategy. Unless otherwise stated, the placement strategy was to select nodes in descending order of degree. The strategy adopted by IAs is that of the secondary convention at timestep 5000. If multiple conventions have the same membership, the one with the highest average adherence is selected.

The IAs remain either indefinitely or for a finite time, to investigate the duration required for destabilisation. When agents cease being IAs they again use Q-learning to choose actions (learning continues whilst they are IAs). Unless otherwise stated, simulations ran for 10000 iterations in total, to give conventions enough time to emerge after destabilisation.

Each agent also has a *cost* associated with it. In order for an agent to be an IA this cost must be paid each timestep. As such, the cost of an intervention is simply the sum of the costs over all IAs for each timestep that the intervention occurs.

When considering the minimum cost of intervening we examine the idea of a *minimum intervention*, the minimum length of time that a given number of agents must remain in the system in order for destabilisation to occur. To quantify this we introduce a new measure: the crossover ratio $\chi_{co}$. The crossover ratio is defined as:

$$\chi_{co} = \frac{memb_{sec}}{memb_{prim}}$$

where $memb_{prim}$ and $memb_{sec}$ are the membership levels of the primary and secondary conventions respectively.

The minimum intervention is the minimum amount of time that a given number of IAs must be introduced to cause $\chi_{co}$ to exceed some threshold, $\gamma_{co}$. In this paper we set $\gamma_{co} = 1.5$ such that the secondary convention must become 50% larger than the primary to be classed as destabilisation.

## V. Results and Discussion

### A. Number of fixed strategy agents

Our initial experiments seek to show that destabilisation is possible and establish the minimum number of IAs required. We begin by considering the setting where IAs remain in the system indefinitely after introduction.

Note that any conventions with near-zero membership have been removed from the following figures for clarity, as they do not affect the emergence exhibited by the system. Conventions are labelled to indicate their relative rankings at timestep 5000.

We begin by considering scale-free topologies. Figure 1 shows the effect on convention membership of introducing IAs. As can be seen in Figure 1a, the addition of 20 IAs causes a drop in the membership of the primary convention after timestep 5000. The size of this drop indicates that the IAs are successful in changing the strategies of agents around them. However, the convention soon stabilises at a new level and the influence of the IAs ceases to spread. The secondary convention never becomes established, as those persuaded to move away from the primary convention did not become strong adherents to the secondary. In comparison, Figure 1b shows that insertion of 40 IAs causes the entire membership of the primary convention to switch, within only 2000 timesteps. These results show that there is a minimum number of IAs required to induce destabilisation. Increasing the number of IAs beyond this minimum was found to accelerate the destabilisation.

The results for small-world topologies (shown in Figure 2) show similar behaviour to that presented above but there are some distinctions to highlight. Firstly, the overall level of membership is lower than in scale-free graphs and, secondly, changes take effect more gradually. Franks *et al.* [2] have observed similar differences between scale-free and small-world topologies. However, as in other topologies, a minimum number of agents is required to cause a destabilisation to occur.

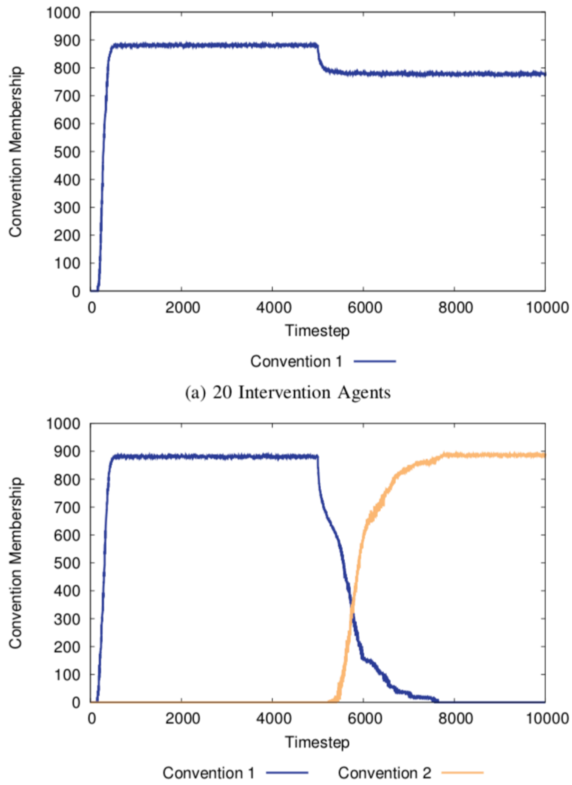



Fig. 1. The effect of IAs on convention membership in scale-free graphs.

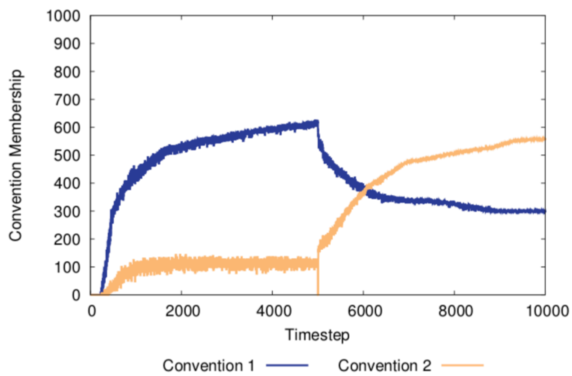



Fig. 2. The effect of 40 IAs in small-world graphs.

Random topologies were also examined but exhibited similar results to scale-free topologies, although requiring more IAs. For space reasons, the results are omitted from this paper.

Within both topologies there is some minimum number of

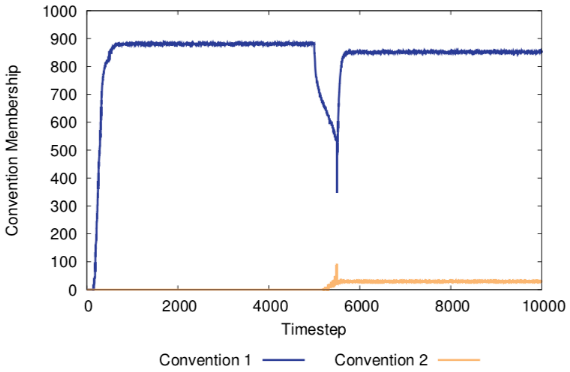



Fig. 3. The effect on convention membership in scale-free graphs of 40 IAs when introduced for 500 timesteps.

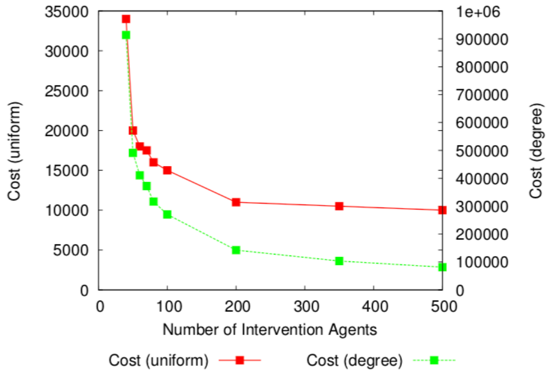



Fig. 4. Number of IAs vs. the minimum cost to cause destabilisation for scale-free topologies. Placement is by degree and the pricing mechanism used is labelled on the graphs.

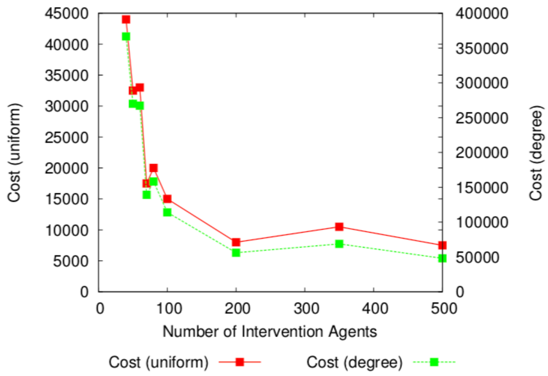



Fig. 5. Number of IAs vs. the minimum cost to cause destabilisation for small-world topologies. Placement is by degree and the pricing mechanism used is labelled on the graphs.

IAs that must be inserted in order for destabilisation to occur. Fewer IAs than this minimum allow the primary convention to stabilise at a lower level whilst additional IAs will increase the speed of destabilisation.

### B. *Length of Intervention*

Whilst IAs remained indefinitely in the previous simulations, we now include them for finite time to find the minimum duration needed for destabilisation. This examines the ability of the primary convention to recover from temporary interventions. Figure 3 shows the effect of including 40 IAs for 500 timesteps and then removing them. Destabilisation begins to occur but, when the IAs are removed, the primary convention rapidly reclaims most of the agents. However, the secondary convention has a small but notable membership after the intervention. This indicates that there is a minimum duration that IAs must be present to prevent the primary convention from recovering. Increasing the length of intervention to 1000 timesteps caused irrecoverable destabilisation. Corresponding results for small-world topologies were also found and showed similar behaviour. The required duration was 1500 timesteps, which is significantly longer and is likely due to the more gradual adoption of change in small-world topologies.

Hence, there is both a minimum number of IAs and a minimum length of time that they must be present in order for them to induce destabilisation. That is, there is a *minimum intervention* within each topology.

### C. *Cost of Intervention*

To examine how the cost of destabilisation relates to the number of IAs used, we calculated the costs of minimum interventions. This was determined by increasing the length of time that the IAs were inserted into the population in steps of 50, starting from 0. For larger numbers of IAs ($\geq 200$) steps of 5 were used, to add finer granularity. The minimum intervention is defined as the smallest insertion time such that the crossover ratio of the averaged runs was greater than $\gamma_{co} = 1.5$. Whilst this is not the true minimum it gives an approximation which is sufficient for our calculations.

Initial experiments used a uniform price for all IAs, with each IA costing one unit per timestep. The number of IAs was varied from 40 (the minimum needed to induce destabilisation in both topologies) up to 500. This is likely to be an unrealistically large proportion in most real-world domains, representing half of the population, but is included for completeness. Uniform cost amongst agents is also potentially unrealistic and so we consider the situation where agents are priced directly based on their degree. Note that in this set of results IA placement is by degree.

Figures 4 and 5 show the results for scale-free and small-world topologies respectively. The cost of minimum intervention for both topologies decreases as the number of IAs increases, following an inverse relationship. Whilst the cost per timestep increases, due to more IAs, the amount of time needed before destabilisation occurs decreases at a faster rate. Whilst both topologies exhibit this behaviour, the cost of minimum intervention in small-world topologies is generally higher than that in scale-free topologies, particularly with smaller numbers of IAs. This is again likely due to convention adoption in small-world topologies occurring at a slower rate than in scale-free networks.

Whilst the scale of the graphs for these results vary, the relationship for each pricing mechanism is similar, with

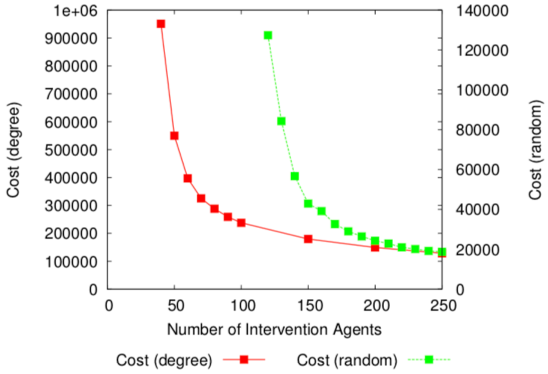



Fig. 6. Number of IAs vs. the minimum cost to cause destabilisation for scale-free topologies. Agents are placed at high cost locations. Pricing mechanisms are indicated on the graph.

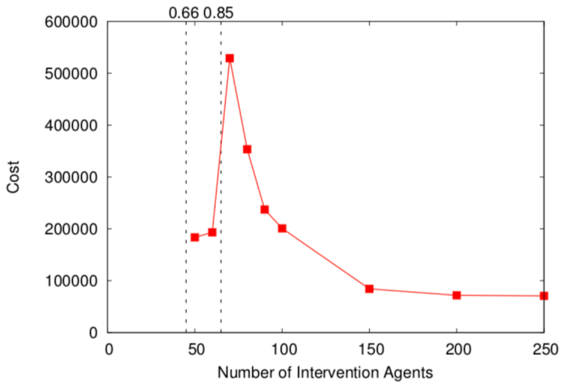
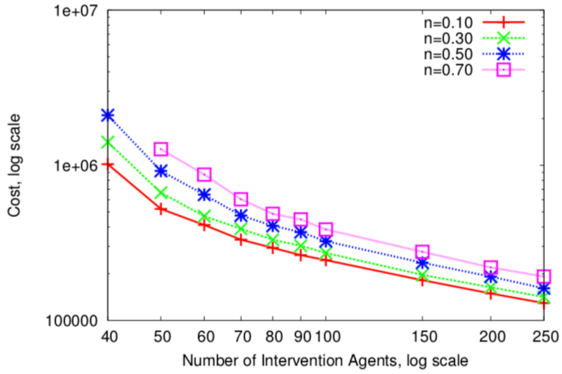
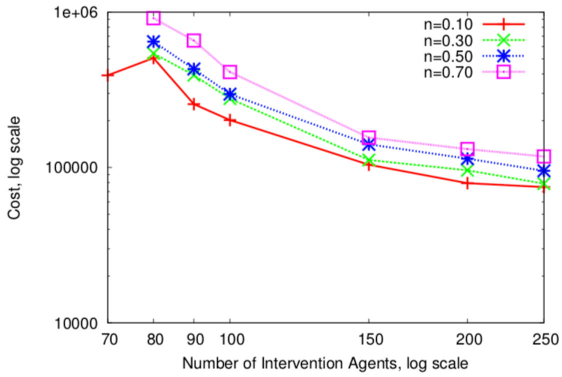



Fig. 7. Number of IAs vs. the minimum cost to cause destabilisation for small-world topologies. Agents are placed at high cost locations. Pricing is by degree.




(a) Scale-free




(b) Small-world

Fig. 8. Number of IAs vs. the minimum cost to cause destabilisation for scale-free topologies. The pricing mechanism is degree with additional noise with IAs placed at high cost locations. Noise is varied from 0.1 to 0.7 in steps of 0.2.

decreasing costs and diminishing returns as the number of IAs increases. This indicates that, regardless of how IA costs are calculated, it is cheaper to place as many IAs as possible into the system at high-degree locations. However the effectiveness of this reduces significantly around 10% of the population.

### D. Cost-based Placement

In the above experiments we assume information about the topology and agent characteristics, such as degree, are available. We now consider the situation where such information is hidden, and all that is known is an *advertised cost* which may or may not be indicative of an agent's influence. In the following experiments, IAs are placed at *high cost* locations, without assuming knowledge of degree.

Our previous experiments also assumed that multiple simulations could be performed ahead of time, to determine the minimum intervention. In real-world settings this is impractical and instead an intervention must be monitored in real-time to establish whether destabilisation has occurred and the IAs can be removed. In the following experiments we use moving averages (window size of 30 timesteps) to calculate $\chi_{co}$ within a simulation. When this exceeds $\gamma_{co}$ destabilisation has occurred, the IAs are removed and the simulation terminated. The cost up to this point represents the cost of a minimum intervention. If this condition is not met by timestep 10000 then the run is deemed unlikely to destabilise and is marked as invalid. We require $2/3$ of the runs to be valid for the minimum interventions to be considered representative and the average minimum cost over the valid runs is then used.

We begin by considering the effect of pricing (and hence placing) agents by degree in scale-free networks, with the results shown by the lower line in Figure 6. We also examine the process of pricing and placing randomly, shown by the upper line. Whilst the relationship between cost and the number of IAs remains, a larger number of IAs is needed to give sufficient valid runs. Importantly, even when placing randomly, we see an inverse relationship regarding the number of IAs and cost.

Figure 7 shows results for small-world topologies and degree pricing. It differs from Figure 5 when the $2/3$ threshold is applied but replicates the shape when a higher threshold is used. This is likely due to higher variance between runs for small-world topologies allowing non-representative runs to be included. Similar results occur for random placement.

Finally we examine the situation where the advertised cost of an agent is an imperfect indication of their degree (and hence influence). This pricing mechanism is useful in domains where agents may be asked to estimate their own influence or domains with unreliable information. This is modelled by selecting each agent's advertised cost from a Gaussian distribution:

$$cost(v) = \mathcal{N}\left(deg(v), (deg(v) \times noise\_level)^2\right)$$

Results for this setting are shown in Figure 8. For both scale-free and small-world topologies the noise level, $n$, was varied from $0.1$ to $0.7$, and the valid run ratio threshold was set to $0.85$ to remove the artefacts present in small-world graphs.

The effect in both topologies of increasing noise is to increase the overall cost that is needed to cause destabilisation. The results are shown on a log-log scale to more easily distinguish this. However, even with 70% noise being applied, the relationship between cost and number of IAs remains the same. As long as the cost is known to be a function of degree, rather than truly random, it is beneficial to base placement decisions on this information even if it is substantially noisy.

Amongst all pricing mechanisms the same inverse relationship between number of IAs and overall cost remains. However, the number of IAs required to consistently cause destabilisation is affected by this mechanism. Hence the best strategy is still to insert as many IAs as possible, using advertised cost if no other metrics are available.

## VI. Conclusions

We have shown that it is possible to cause destabilisation of existing conventions by the insertion of a small proportion of fixed strategy *Intervention Agents* into the population at key locations. By setting the strategy of these agents to that of the second largest convention we have shown that the primary convention can be destabilised and replaced with the secondary. In scale-free and small-world topologies we found that 40 IAs in a population of 1000 were sufficient to cause this. Fewer IAs than this were shown to cause a fall in the membership of the primary convention in each topology, but not enough to make the secondary convention dominant.

We have also shown that temporarily inserting IAs can also cause destabilisation, and that there exists a minimum length of time that they must be present in order to cause this. Removing IAs prior to this minimum duration will cause the primary convention to return to near previous levels. We found that the minimum length of time required was smaller in scale-free topologies than small-world topologies.

Next we considered the cost of these interventions, and show that, independent of whether cost is uniform or linked to degree, the cost of minimum intervention is inversely related to the number of IAs. However, the relationship is one of diminishing returns. As such, placing as many IAs as possible into the system is beneficial but the additional effect generated reduces substantially after 10% of the population.

Finally, we explored the effect of placing IAs by cost and monitoring destabilisation in real-time. The same relationship between number of IAs and cost was found to hold regardless of pricing/placement mechanism although higher numbers of IAs may be needed to sufficiently guarantee destabilisation. We also found that small-world topologies vary in this respect more between simulations than scale-free networks. The effect of noise on the degree-based pricing mechanism was also considered. It was found, for both topologies, that the effect of noise was to increase the overall cost of minimum interventions but to not affect the relationship between cost, the number of IAs, and the duration of minimum interventions. We conclude from this that placing by advertised cost would offer reasonable results, assuming non-random pricing.

Overall we have shown that destabilisation and replacement of an established convention is possible and that minimum criteria exist in order to cause this. We have also presented a number of ways of evaluating how much an intervention might cost using various pricing methods and demonstrated the relationship between the number of IAs and cost.

## References


[1] J. Delgado, J. M. Pujol, and R. Sangüesa, "Emergence of coordination in scale-free networks," *Web Intelli. and Agent Sys.*, vol. 1, no. 2, pp. 131–138, 2003.

[2] H. Franks, N. Griffiths, and A. Jhumka, "Manipulating convention emergence using influencer agents," *Autonomous Agents and Multi-Agent Systems*, vol. 26, no. 3, pp. 315–353, 2013.

[3] J. Kittock, "Emergent conventions and the structure of multi-agent systems," in *Lectures in Complex Systems: the Proc. of the 1993 Complex Systems Summer School*. Addison-Wesley, 1995, pp. 507–521.

[4] S. Sen and S. Airiau, "Emergence of norms through social learning," in *Proceedings of the 20th International Joint Conference on AI*. Morgan Kaufmann Publishers Inc., 2007, pp. 1507–1512.

[5] D. Villatoro, S. Sen, and J. Sabater-Mir, "Topology and memory effect on convention emergence," in *Proc. of the 2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology*. IEEE Computer Society, 2009, pp. 233–240.

[6] N. Griffiths and S. S. Anand, "The impact of social placement of non-learning agents on convention emergence," in *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2012, pp. 1367–1368.

[7] H. P. Young, "The economics of convention," *The Journal of Econ. Perspectives*, vol. 10, no. 2, pp. 105–122, 1996.

[8] D. Villatoro, J. Sabater-Mir, and S. Sen, "Social instruments for robust convention emergence," in *Proc. of the 22nd International Joint Conference on AI*. AAAI Press, 2011, pp. 420–425.

[9] A. Walker and M. Wooldridge, "Understanding the emergence of conventions in multi-agent systems." in *International Conference on Multi-Agent Systems*. MIT Press, 1995, pp. 384–389.

[10] Y. Shoham and M. Tennenholtz, "On the emergence of social conventions: modeling, analysis, and simulations," *Artificial Intelligence*, vol. 94, no. 1–2, pp. 139–166, 1997.

[11] J. Delgado, "Emergence of social conventions in complex networks," *Artificial Intelligence*, vol. 141, no. 1–2, pp. 171–185, 2002.

[12] N. Salazar, J. A. Rodriguez-Aguilar, and J. L. Arcos, "Robust coordination in large convention spaces," *AI Commun.*, vol. 23, no. 4, pp. 357–372, 2010.

[13] H. Franks, N. Griffiths, and S. S. Anand, "Learning agent influence in MAS with complex social networks," *Autonomous Agents and Multi-Agent Systems*, pp. 1–31, 2013.

[14] J. Marchant, N. Griffiths, M. Leeke, and H. Franks, "Destabilising conventions using temporary interventions," in *Proceedings of the 17th International Workshop on Coordination, Organizations, Institutions and Norms*, 2014.

[15] R. Albert and A.-L. Barabási, "Statistical mechanics of complex networks," *Rev. of Mod. Phys.*, vol. 74, no. 1, pp. 47–95, 2002.

[16] J. Kleinberg, "Navigation in a small world," *Nature*, vol. 406, no. 6798, pp. 845–845, 2000.