SumUp 23-10-2020

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I. Experiments Presentation

The goal of this document is, to sum up, and describe the experiments done up to now. All the experiments were done using the software in this repository and are fully replicable. How to run and analyze the experiments is out of the scope of this document.

The experiments are divided in two main categories:

- ***Single node evaluation***, in this group of experiments the goal is to analyze a single node evolution in the network;
- ***Network evaluation***, in this group of experiments the evaluation is done on the entirety of the network.

II. Goals

Like I specified in Section I all the experiments are divided into two categories that are distinguished by the size of the analysis. The simulation environment could be the same but the difference is in the analysis of the evolution.

In the first case, ***Single node evaluation***, the goal of the analyzer is to study a specific node and highlight the evolution of it. The output of the analysis could be the Finite State Machine (FSM) of the node and the signalling plot.

The signalling of a node represents all the possible outputs of a node. A single output signal represents in a single experiment the messages transmitted by the node, the result will be a mix of advertisements and withdraws in a string like "A1W1A4A6W6" This ouptuts signals, for each bunch of experiments, are collected in a CSV file with the appearance frequency of each output signal.

In the second case, ***Network evaluation***, we are looking for network results, evaluating the entire set of nodes and links. This is done by studying the number of messages transmitted and the convergence time.

Given T_{tx} as the time of the first transmission and T_{rx} as the time of the **last** reception the convergence time, CT, is given by the delta of those times: $CT = T_{rx} - T_{tx}$. The convergence is reached when the network becomes silent again.

III. Environments

Multiple environments have been used for the experiments. The main differences and properties of those environments are described in this section.

The first environment that I used is a *Fabrikant* environment with different Minimum Route Advertisement Interval (MRAI) settings. This name comes from the particular graph used, described in Section IV. The four types of MRAI used are:

- ***Fixed 30s***, MRAI is fixed for each link to 30 seconds;
- ***No MRAI***, MRAI is fixed for each link to 0.0 seconds;

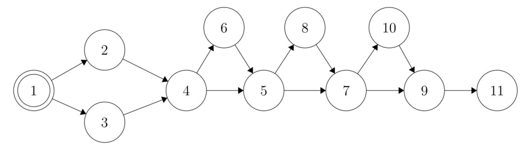


Figure 1: Fabrikant graph representation

- ***Ascendent***, MRAI will be doubled at each leach ($1-2-4-8-...$);
- ***Descendent***, Reverse of the ascendent case, MRAI will be divided by two at each leach.

The second environment used is a *clique* one, the graph is described in Section IV, all the parameters of the environment are described in Section V In all the clique experiments MRAI has been fixed in all the links. For each value of MRAI has been done 10 different experiments and MRAI goes from 0 in the first group of experiments to 60 in the last group. For a total of 610 runs in this topology.

The last one used is an *Internet Like* environment. The graph is described in Section IV, all the parameters are described in Section V. The main goal of this environment was to emulate, roughly, a real environment. The main difference between different experiments on this environment was the type of MRAI applyed:

- ***Random MRAI***, for each link the MRAI value will be chosen with a uniform distribution between $[0.0, MRAI_{limit}]$, the network must respect a defined $MRAI_{mean}$ value
- ***Fixed MRAI***, for each link the MRAI will be equal to $MRAI_{mean}$
- ***DPC***, for each link the MRAI will be setted according to the centrality of the node, process described in Section VI

In this environment has been run multiple experiments for each MRAI type. For each experiment, a new graph would be computed, so in the *Random MRAI*, for the same $MRAI_{mean}$ value could exists multiple different graphs.

IV. Input Graphs

In total three different base graphs has been used to produce all the results in this document.

A. Fabrikant Graph

The Fabrikant graph replicate what is described in the first figure in [1]. for simplicity, an example is reported here in Figure 1

Node 1 represent the only source of traffic, node 4 will prefer to reach the destination through node 2, but the link is slower, triggering changes in the network as required by [1].

Taking this base frabrikant graph other 4 graphs has been deveolped, one for each MRAI strategy applyed.

B. Clique Graph

The clique graph used for the clique experiemnts is composed of 15 nodes plus one external node that is the source of a destination. Each node is connected to every other node in a mesh network. The only node that does not respect this rule is the destination source. it has only one link that is connected to the node of the mesh network number 0.

Relationships between nodes are of the servicer type, so each node has 14 clients to updated when it receives an update. This ensures that the information is shared in the entire network.

For this network has been generated one graph for each fixed MRAI used, so that at the end we had 60 different clique graphs with the correct timer value equal on each link.

C. Internet Like Graph

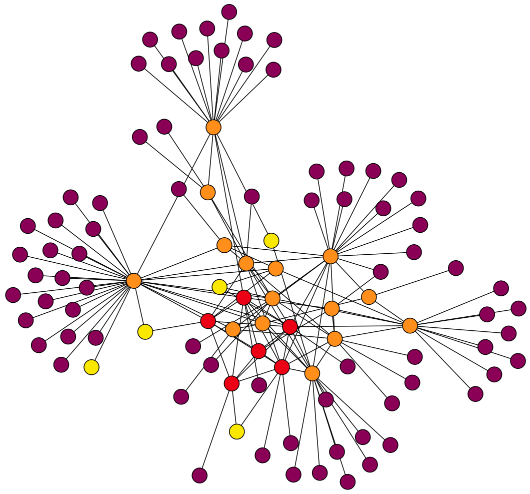
This network is composed of 100 nodes, it is not enough to emulate the Internet but, with enough computation time, the results should be comparable with bigger graphs. The graph has been produced following [2].

In the graph has been chosen only one node that shares a destination. The node has been chosen randomly in the set of clients nodes.

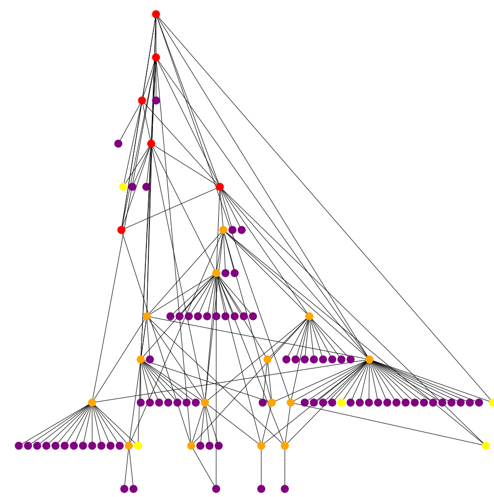
For each experiment, depending on the type of MRAI, a new graph file has been generated with different MRAIs values on the edges.

In total has been generated 10 000 internet like graphs.

The base graph is represented in Figure 2. The figure include two different layout of the graph, to show the hierarchical structure. Central nodes (red nodes) represent the tier one nodes, and them compose a little mesh network at the highest level of the network. Other types of nodes could be M, CP or C, the las category is the one representing the clients that can't do peering with other nodes and them are the magiority of the nodes. The random node that share a destination is chosen in the C set.



(a) Internet like graph with an "explosive" layout



(b) Internet like graph with a "hierarchical" layout

Figure 2: Internet like graph colored to show the hierarchicaly structure, 4 tipes of nodes, T (tier 1 mesh), M, CP, C (Customers, purple one)

V. Input arguments

In this section are described the inputs arguments used for the different environments.

A. Fabrikant arguments

- seeds: 20 different seeds;
- Signaling: "AWA", The input signal determines the messages that the source should send
- Implicit withdraw: active
- Withdraw distributions: 3 different withdraw uniform distributions $[5, 10]$, $[10, 15]$ and $[30, 45]$
- Reannouncement distributions: 3 different announcement uniform distributions $[5, 10]$, $[10, 15]$ and $[30, 45]$
- Processing time: constant with value $0.000\,01$
- Network delay: 3 uniform distributions in $[0.001, 1]$, $[0.5, 3]$ and $[2, 6]$

The number of possible different combinations of these values is 540, so for each different MRAI type has been done 540 experiments and in total 2160 expieriments in the fabrikant environment.

B. Clique arguments

- seeds: 10 different seeds;
- Signaling: "AW"
- Implicit withdraw: active
- Withdraw distributions: uniform distribution $[5, 10]$
- Reannouncement distributions: Ininfluent
- Processing time:i uniform distribution $[0.01, 1]$
- Network delay: uniform distribution in $[0.012, 0.1]$

This environment attempt to replicate what has been presented in [3]

In total this environment would run 10 different permutations because the only element that can differ is the input seed. But has been done in a total of 61 experiments changing the MRAI value between 0 and 60, so in total, we had 610 runs, 10 for each MRAI value. It wouldn't have much sense, in my opinion, to run more than one simulation batch per MRAI value, because the repetition of the seed with no difference in any other parameter would have produced the same result. For comparison purposes the same environemnt has been run even with the implicit withdraw option deactivated.

C. Internet like arguments

- seeds: 10 different seeds;
- Signaling: "A"
- Implicit withdraw: active
- Withdraw distributions: Ininfluent
- Reannouncement distributions: Ininfluent
- Processing time: constant with value $0.000\,01$
- Network delay: uniform distribution in $[0.012, 3]$

The environment has been used for random experiments and fixed mrai experiments.

Like in the clique experiments, in the case of the fixed MRAI, every link had the same timer value. But this time has been used also fractions of seconds to highlight the trend. There have been 121 experiments with MRAI in the ensemble $[0.0, 60]$. In the first fraction $[0.0, 5.0]$ has been used a step of 0.1 doing 51 experiments. The second fraction was $[5.5, 20]$ with a step of 0.5, doing in total 30 experiemnts. The last subset was $[21, 60]$ with a step of 1, doing in total 40 experiments. The final total is 121 experiments and for each of them has been done 10 runs, one for each possible seed of the environment.

For comparison purposes the same environemnt has been run even with the implicit withdraw option deactivated.

The second type of experiments with the internet like environemnt were run with the Destination Partial Centrality (DPC) MRAI strategy. This centrality metric si explained in Section VI, it's applyed on every edge of the network considering three phases in the graph. Then I applied the same $MRAI_{mean}$ sequence that was described for the constant MRAI experiments, so in total we have 121 experiments.

For comparison purposes the same environemnt has been run even with the implicit withdraw option deactivated.

The last type of experiments with the internet like environment were run with random graphs. Before running a random experiment the $MRAI_{mean}$ were chosen randomly before the generation of the random graph. In total has been chosen 100 random $MRAI_{mean}$ uniformly distributed in the set $[0, 60]$ the limit 60 has been chosen arbitrarily being the double of the actual standard. 100 random graphs were generated for each $MRAI_{mean}$. Each link would obtain a random value in the set $[0, 240]$ and then all the values would be re-proportioned to respect the $MRAI_{mean}$ At the end for each random graph would be done 10 runs thanks to the 10 different seeds. The total number of this particular configuration is $100 * 100 * 10$ equal to $100\,000$ single runs.

VI. Destination Partial Centrality

In this section I will define and explain how was applyed the DPC in the experiments. What follow has been taken from [4].

The intuition at the base of centrality-based MRAI tuning is that we would like MRAI to increase in the initial phase, close to Tier one nodes set (from now on T_R set), and then, when the core of routers around T_R stabilized, it should start decreasing in order to quickly propagate the new stable situation to the rest of the Internet. To verify the validity of this intuition we set-up a strategy that exploits the previous knowledge of the network graph together with the concept of Destination Partial Centrality (DPC).

DPC is a variant of so-called load centrality which is defined in its general form as follows [5]: Consider a graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ and an algorithm to identify the (potentially multiple) minimum weight path(s) between any pair of vertices s, d. Let $\theta_{s,d}$ be a quantity of a generic commodity that is sent from vertex s to vertex d. We assume the commodity is always passed to the next hop following the minimum weight paths. In case of multiple next hops, the commodity is divided equally among them. We call $\theta_{s,d}(v)$ the amount of commodity forwarded by vertex v. The *load centrality* of v is then given by:

$$LC(v) = \sum_{s,d \in \mathcal{V}} \theta_{s,d}(v) \qquad (1)$$

DPC adapts load centrality to represent the propagation of routes in an IP network. In DPC *load* represents the amount of networks that a BGP node exports. Not all nodes that run BGP generate *load*, but all nodes that forward traffic have a non-zero DPC centrality. We call $\mathcal{C} \subseteq \mathcal{V}$ the set of nodes that can be source and/or destination of traffic (they export at least one network) and N_s, N_d the number of networks that are exported by node s and d, respectively, then $\theta_{s,d} = \frac{N_s + N_d}{2}$. DPC $\Delta(v)$ of any vertex $v \in \mathcal{V}$ is defined as

$$\Delta(v) = \sum_{s,d \in \mathcal{C}} \theta_{s,d}(v) \qquad (2)$$

With DPC we model the fact that some Internet routers export network addresses, and for this reason they generate changes in the network state, while other routers only forward traffic, but still their centrality can be larger than zero.

In a previous work we have shown that load centrality can be computed in a distributed way with minimal modifications to a Distance-Vector routing protocol. We also experimentally verified that computing DPC is possible with a custom BGP extension, and thus, it can be incrementally deployed on the Internet without requiring any global coordination [1]. Further theoretical details are outside the scope of this paper, but principles of centrality-based routing can be found in [6], [7].

Our proposal configures MRAI as a function of DPC with the following model: We assume the information contained in the `UPDATE` message propagates in the network in three phases, which identify three propagation graphs:

- ***Ascending phase graph*** $\mathcal{G}_{\mathcal{A}}(\mathcal{V}^{\mathcal{G}_{\mathcal{A}}}, \mathcal{E}^{\mathcal{G}_{\mathcal{A}}})$*:* made by the nodes updated without reaching tier one nodes;
- ***Tier one graph*** $\mathcal{G}_{\mathcal{T}}(\mathcal{V}^{\mathcal{G}_{\mathcal{T}}}, \mathcal{E}^{\mathcal{G}_{\mathcal{T}}})$*:* made by tier-1 nodes;

[1] A brief explanation on how to calculate in a distributed way the centrality can be found at: https://iof.disi.unitn.it/docs/DPCOnTopOfBGP.pdf

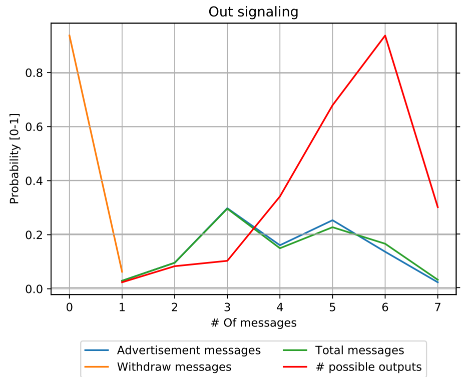


Figure 3: Fabrikant MRAI fixed 30 seconds, node 9 signalling output

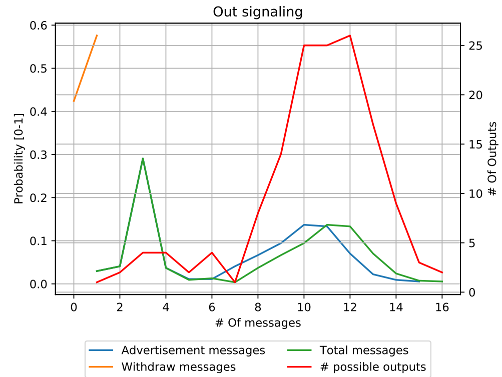


Figure 4: Fabrikant MRAI descendent, node 9 signalling output

- ***Descending graph phase*** $\mathcal{G}_\mathcal{D}(\mathcal{V}^{\mathcal{G}_\mathcal{D}}, \mathcal{E}^{\mathcal{G}_\mathcal{D}}) = \mathcal{G}(\mathcal{V}, \mathcal{E}) - \mathcal{G}_\mathcal{A}(\mathcal{V}^{\mathcal{G}_\mathcal{A}}, \mathcal{E}^{\mathcal{G}_\mathcal{A}}) - \mathcal{G}_\mathcal{T}(\mathcal{V}^{\mathcal{G}_\mathcal{T}}, \mathcal{E}^{\mathcal{G}_\mathcal{T}})$*:* the rest of the graph.

Considering a graph-wide maximum timer $T = 30\,\mathrm{s}$ and DPC $\Delta(i) \in [0, 1]$ for node i, DPC-based MRAI T_{ij} used by node i with neighbor j is set as follows:

$$T_{ij} = \begin{cases} \frac{T}{2}\Delta(i) & \forall i \in \mathcal{V}^{\mathcal{G}_\mathcal{A}} \\ \frac{T}{2} & \forall i \in \mathcal{V}^{\mathcal{G}_\mathcal{T}} \\ \frac{T(1-\Delta(i))}{2} + \frac{T}{2} & \forall i \in \mathcal{V}^{\mathcal{G}_\mathcal{D}} \end{cases} \quad (3)$$

VII. Experiments Results

The first results that I would like to examine is the single node results from the fabrikant experiment. In Figures 3 and 4 are represented two signalling outputs of the node number 9.

The x axis represents the number of messages in the output signal. The first y axis, the one on the left, represents the probability to have a certain number of messages in the output sequence and should be used with "withdraw messages", "Advertisement messages" and "Total messages" lines. For example in Figure 3 we can see that there is a really high probability to have 0 withdraws in the output sequence, and we would never see more than 1 withdraw by the fact that the "withdraw line" doesn't go over that value of the x axis. In the same way, we can read the other lines, for example in the same figure is possible to see that the more probable output signal is composed by 3 messages, because is the highest point of the blue line. The second y axis, the one on the right, represents the number of **unique** states. This axis should be used with the line that represents the "possible outputs". Looking the Figure 3 is possible to see that for output signals with 6 messages we have more than 40 uniques output states.

Knowing that the output signalling is strictly dependent by the input that a node receives and the evaluation time of those messages we can already see the effects of an inconvenient MRAI setting. In Figure 4 there are a lot more output states. In those experiments we reach event output states of length 16 and the probability to have at least one withdraw is higher to the probability to don't have one. Knowing that the implicit withdraw system is active having one withdraw means that the node has no other possibilities to withdraw the network not knowing any other path.

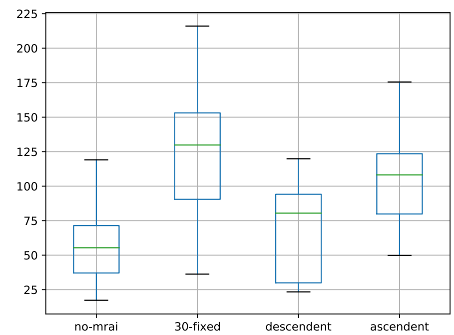


Figure 5: Fabrikant experiments convergence time comparison

Like we said before we used 4 different MRAIs strategies in the fabrikant environment, and them are compared in the Figures 5 and 6. The no mrai method is strictly dependent on delays and other events of the network and is possible to see that it has the smallest convergence time but with the higher number of messages necessary to reach the convergence. The 30 seconds strategy could be the slowest one because if something goes wrong is necessary to wait a long time to repair the damage, but it wouldn't require too many messages on the other side. The descendant method seems a good solution on the convergence time side, but on the other side, like is described in [1] it could easily lead to a lot of messages.

In Figures 7 and 8 are reported the general network results

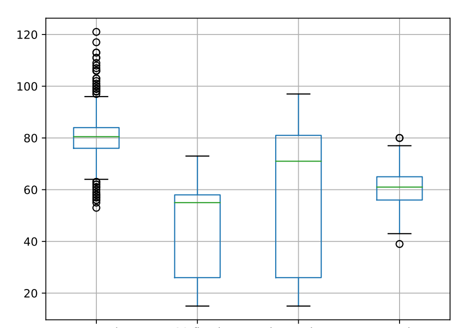


Figure 6: Fabrikant experiments number of messages comparison

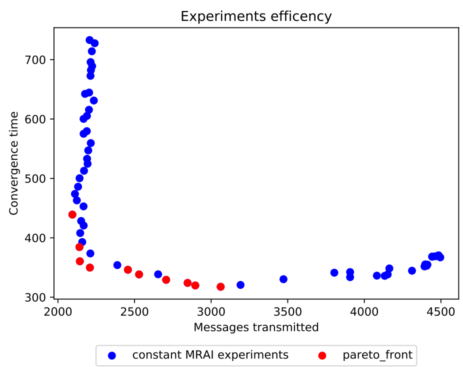
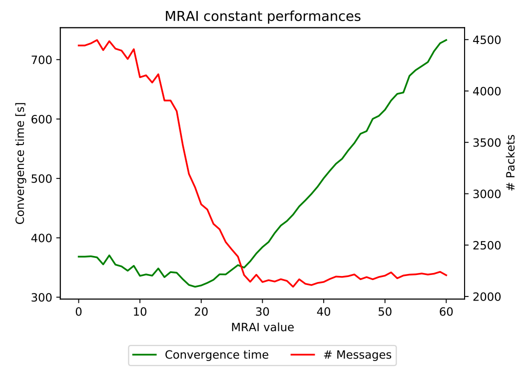
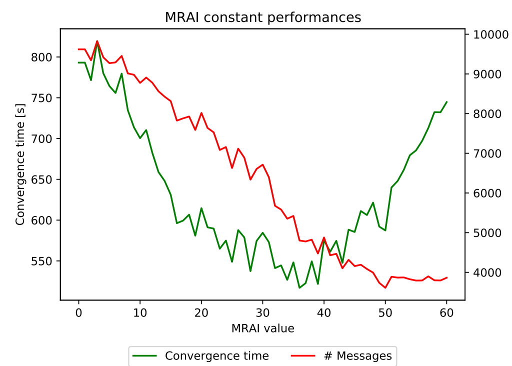


Figure 7: Pareto front in the clique environments



(a) Clique environment with Implicit Withdraw active



(b) Clique environment **without** Implicit Withdraw active

Figure 8: Evolution of the number of messages sent and the convergence time as MRAI grows in the clique environment

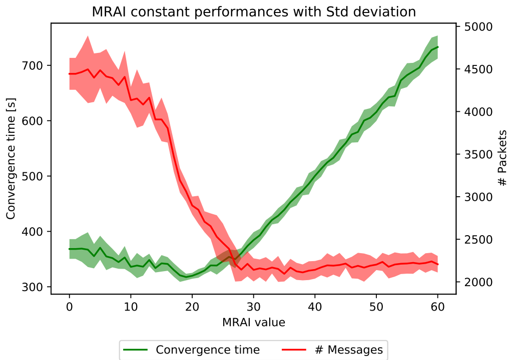
obtained in the clique environment. The goal of this study is to see in a general way how MRAI could influence even a small network as this clique of 15 nodes.

In Figure 7 every point of the plot is the mean of the 10 runs executed with a fixed MRAI. On the x axis is represented the number of messages correlated with the convergence time on the y axis. The red points are the Pareto front of the set of all points. We can see from the plot that a lot of experiments has a mean of messages sent around 2000 independently from the MRAI so we can guess that after a threshold of MRAI the number of messages stabilizes around that value. On the other side, before this threshold we can guess there is a lot of variance in the number of messages but the mean convergence time is similar. These guesses are confirmed by the Figure 8a where we can clearly see those trends. The two y axis are used to represent the trend of the convergence time and the number of messages transmitted in relation of the MRAI value. The two Figures 8a and 8b refers to two different situations in the same clique graph. In the first figure the implicit withdraw is active, in the second has been deactivated, the difference is evident, the number of messages and the convergence time are higher without the implicit withdraw active, and also take a longer time to reach a stable point in Figure 8b. This confirm what has been presented in [8].

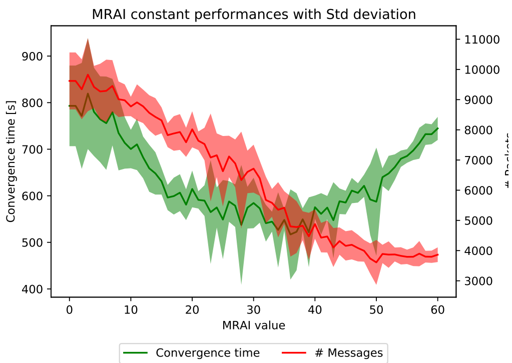
On the same environemnt I have produced also two more plots that are presented in Figure 9, the plots represent the same trend of Fig. 8 but this time there is a range around the lines that represent the standard deviation of every experiment (each experiment point is the mean of 10 runs). In Figure 9a is possible to see that with a small MRAI the standard deviation is higher respect to the standard deviation after a certain threshold of MRAI. The standard deviation of both messages and convergence time seems to be constant after a certain threshold. In Figure 9b is not possible to see clearly the same trend in the standard deviation, but with an MRAI higher than 50 is possible to guess that the standard deviation is starting to be more constant. Figure 9b confirms another time that without the implicit withdraw the number of messages and the convergence time would be a lot more suceptible and unpredictable.

The next experiment that I would like to study uses the fixed MRAI strategy on the internet like environment. The two Figures 10 and 11 have the same structure of the clique results but this time we can see a lot fewer messages transmitted to reach the convergence. Also this time we can see in Figure 10 that a lot of experiments are concentrated in the range between 146 and 147 messages with a high variance on the convergence time. In fact, we can see from Figure 11 that the trend is similar to the one that we saw in the clique graph, but this time the "# Messages" line has a steep fall, it reaches the constant state in few seconds (the clique experiment in Figure 8 took more than 20 seconds). But we can say the same thing for the convergence time too. Tose results are similar to the one available in [3]. With an MRAI lower than 1 s the number of messages could have huge spikes because the network delay is more influent than the timer. In fact, after a certain MRAI threshold the network delay becomes ininfulent and the number of messages strictly depend on the order of events that can produce constructive messages or disruptive that will be corrected in the next MRAI cicle. And this is the reason for the constant growing of the convergence time, it will takes always a higher time to correct incorrect messages.

The trend showed Figures 11a and 11b is comparable, in Figure 11b we can see that it requires more messages to reach the convergence but not more time. And the message trend



(a) Clique environment with Implicit Withdraw active



(b) Clique environment **without** Implicit Withdraw active

Figure 9: Evolution of the number of messages sent and the convergence time as MRAI grows in the clique environment, the range around the line represent the standard deviation of the experiment

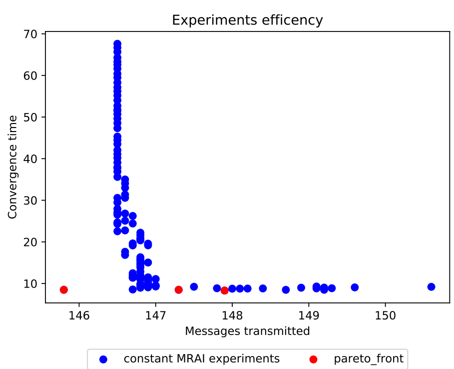
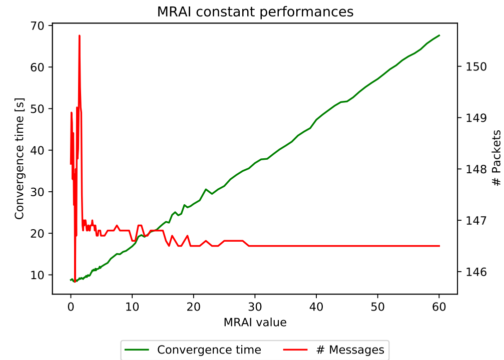


Figure 10: Pareto front in the Internet like constant MRAI environment

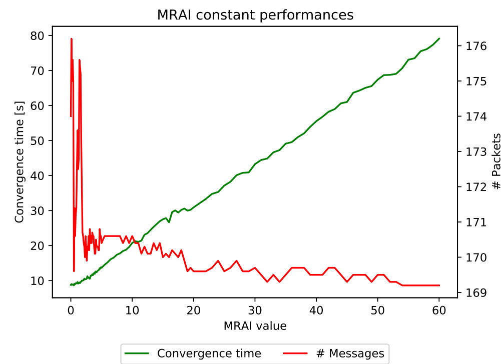
took more time to become stable.

Like before in Figure 12 is possible to compare the two techniques (Implicit Withdraw active, vs IW deactivated) with also the standard deviation of the experiments. Each point of the line is the mean of 10 runs, the standard deviation is calculated on those runs, those runs are just a subset of the infinite population of possible outputs.

The first thing that we can see in both figures is that the standard devition around the messages lines is constant for the majority of the time, execpt for a small MRAIs that produces



(a) Internet like constant MRAI environment with Implicit Withdraw active



(b) Internet like constant MRAI environment **without** Implicit Withdraw active

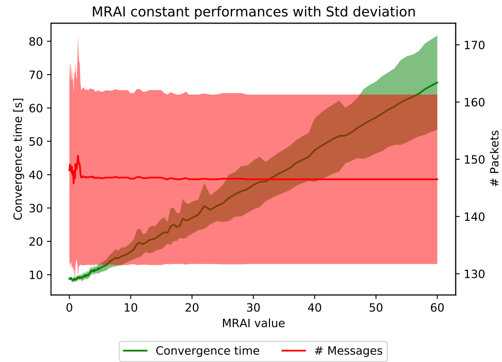
Figure 11: Evolution of the number of messages sent and the convergence time as MRAI grows in the **internet like** constant MRAI environment

huge spikes of variation. This effect is caused, like we said before, by the fact that after a certain MRAI threshold, the order of the events is the only factor that influence the number of messages. In all this experiments the only thing that changes was the MRAI value, so the order of events is the same (given by the seed of the RNG), and, given the ininfluence of MRAI, produces the same number of output messages in each run. It follows that that the standard deviation of each experiment is the same.

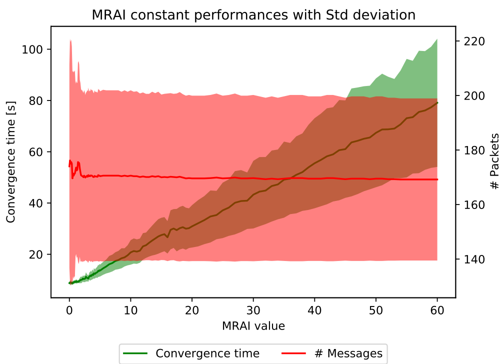
We have to remember that with the implicit withdraw feature are produced less messages by assumption, so we can't compare the number of messages or the standard variation of those thrends one another.

But, the convergence time is comparable. We can clearly see that the standard deviation of the time trend in Figure 12a is lower than the one in Figure 12b. I guess this difference is caused by the fact that huge storms of withdraws must be processed and eventually forwarded, causing more computation time and the forwarding of packets that don't give new knowledge at the neighbors. Packets that occupy a position in a FIFO link and with a delay.

I done the same experiments in the internet like environment



(a) Internet like constant MRAI environment with Implicit Withdraw active, standard deviation



(b) Internet like constant MRAI environment **without** Implicit Withdraw active, standard deviation

Figure 12: Evolution of the number of messages sent and the convergence time as MRAI grows in the **internet like** constant MRAI environment. The range around the lines represent the standard deviation of the experiment FiXme: Look for a bug in the standard deviation of messages

with the DPC MRAI strategy. The number of experiments and the sequence of $MRAI_{mean}$ tested is the same as the constant MRAI.

Is possible to see in Figure 13 that the distribution is similar to the one in Fig. 10, but this time the spike of vertical values is around the messages value 149 with pratically no variation between one experiment and another. The horizontal spike this time is on the left of the vertical spike, and this is important because it represent that is more rare to go over that value of messages sent.

Like before we can guess that there will be some MRAI thresholds for the two spikes.

Once again the guess on the threshold is confirmed by Figure 14 plots where is possible to see that on low MRAI values we will have a huge variation on the number of messages distributed, but once the threshold is crossed the number of messages will be constant. And this time if we compare Figure 14a with Figure 11a we will see that with the DPC techinique this threshold is crossed way before. Is also noticeable that once the threshold is crossed there are no stability issues on the number of messages. exept for the Figure 14b plot where we can see some small variation on the stabilized number of messages.

Like before in Figure 15 is possible to see the DPC MRAI strategy experiments on the internet like evironment with the standard deviation.

Like before the number of messages has a constant standard deviation after the threshold thanks to the event sequence.

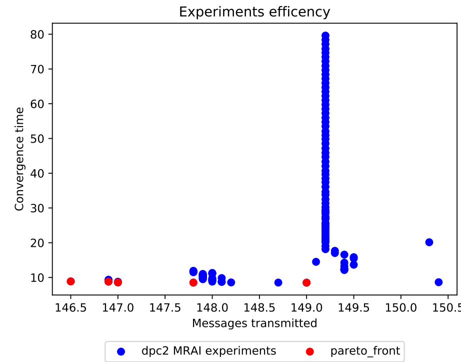
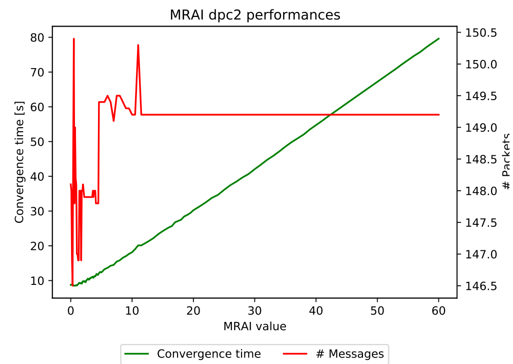
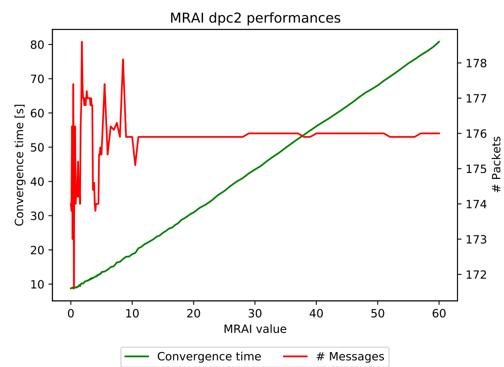


Figure 13: Pareto front in the Internet like DPC MRAI environment, IW active

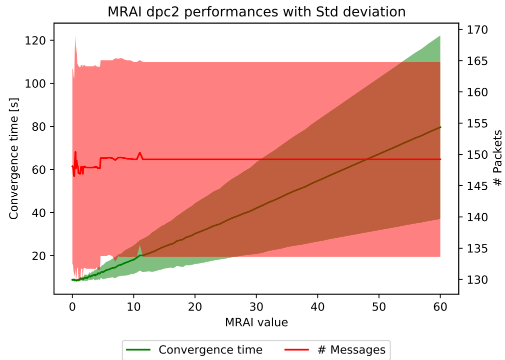


(a) Internet like DPC MRAI environment with Implicit Withdraw active

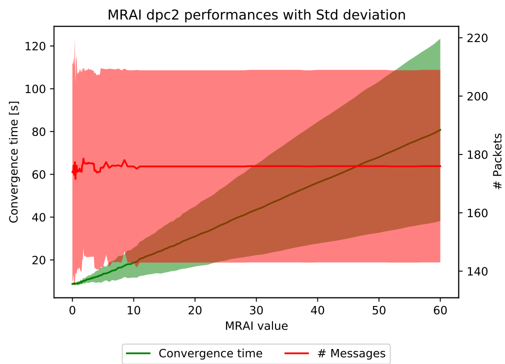


(b) Internet like DPC MRAI environment **without** Implicit Withdraw active

Figure 14: Evolution of the number of messages sent and the convergence time as MRAI grows in the **internet like** constant MRAI

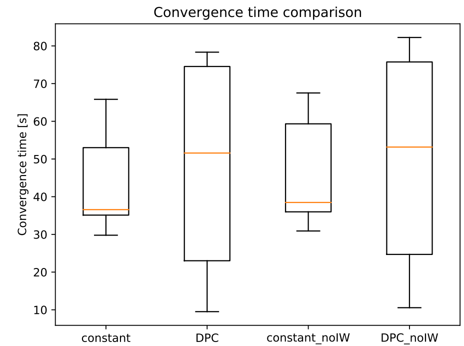


(a) Internet like DPC MRAI environment with Implicit Withdraw active, standard deviation

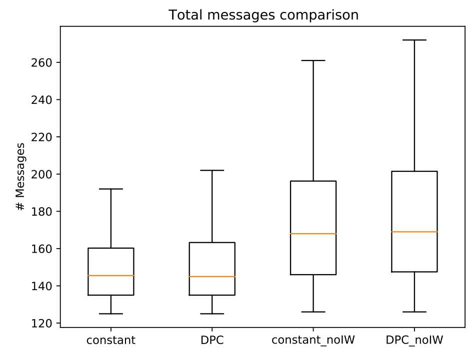


(b) Internet like DPC MRAI environment **without** Implicit Withdraw active, standard deviation

Figure 15: Evolution of the number of messages sent and the convergence time as MRAI grows in the **internet like** DPC MRAI environment. The range around the lines represent the standard deviation of the experiment FiXme: Look for a bug in the standard variation



(a) Convergence time comparison between different environments



(b) Messages necessary to reach the convergence comparison

Figure 16: Comparison between the DPC MRAI strategy and the constant MRAI strategy, 100 experiments with the same conditions with $MRAI_{mean}$ equals to 30.0

The two plots respectively in Figures 15a and 15b are similar one another, execpt for the number of messages transmitted that it's not comparable. The big difference that we can see from the constant MRAI experiments is that the standard deviation around the time, in the DPC MRAI strategy, is bigger than the other. An educated guess could be that we can have a lower convergence time because MRAI is higher only where necessary and correct informations would travel faster around the network. On the opposite side bad informations could spread too, generating the opposit case with an high convergence time, caused by the fact that take more time to make every node converge.

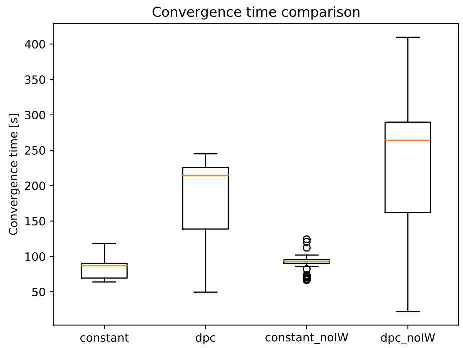
I then decide to take a look more closely to those MRAI strategies that we just saw. This time with $MRAI_{mean}$ fixed to 30 s for every MRAI strategy. I fixed the graph, using the internet like graph of the internet like environment. I increased the number of seeds that would be given to the random number generator of the des, so I was able to run 100 runs for each MRAI strategy. So I have done 100 runs for constant MRAI (with implicit withdraw and without) and 100 runs for the DPC technique (with and without implicit withdraw). The results are showed in Figure 16.

In Figure 16a are presented the boxplot to compare the convergence time of the experiments sets. The first thing that is possible to notice is that in the constant case the difference caused by the use of the implicit withdraw is marginal, just few seconds. On the other side, with the DPC the difference is huge. With the IW active, like we said before, we can reach a small convergence time thanks to positive information dissemination, but in case of disruptive messages this is can cause the opposite situation.

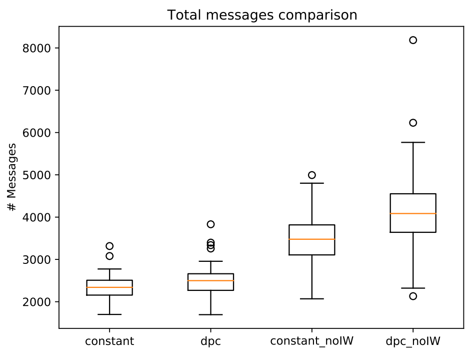
I have to say that I guess this situation is amplified by the fact that we are using a small graph not representative of the internet with a lot of nodes with MRAI setted to 0 sharing a lot of disruptive information without waiting enough.

So i decided to run the same experiments on an internet like topology of 1000 nodes. Always with $MRAI_{mean}$ of 30 and 100 different seeds. The results are presented in Figure 17.

Some more general results could be saw taking into consideration the random MRAI strategy on the internet like graph. The results are visible in Figure 18. The first thing that we can see is that this time there are not huge spikes for certain messages amount. The number of messages is more distributed



(a) Convergence time comparison between different environments



(b) Messages necessary to reach the convergence comparison

Figure 17: Comparison between the DPC MRAI strategy and the constant MRAI strategy, 100 experiments with the same conditions with $MRAI_{mean}$ equals to 30.0, in an internet like graph with 1000 nodes FiXme: check if the constant-noIW is correct

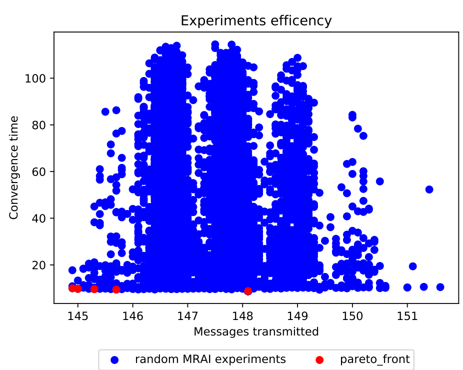


Figure 18: Pareto front in the Internet like random environment

between 145 and 152, with some particulary dense columns. Also, the convergence time is more distributed, thanks to the random MRAI distribution. We can guess that if a central node has a huge MRAI timer and it transmits incorrect information it would act as a bottleneck for the update with the correct information.

From the comparison of the three MRAI strategies we can see, in Figure 19, that the constant MRAI covers a really small part of the random strategy, and it has the tendency to produce

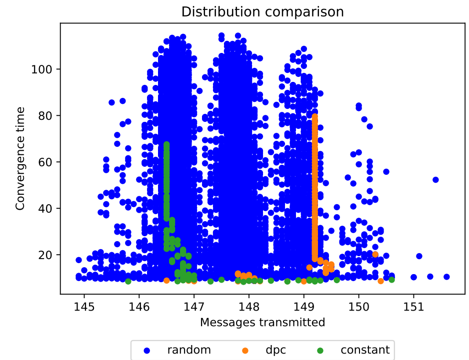


Figure 19: Comparison of the random strategy and the constant one in the internet like environment

a lot of messages for low $MRAI_{mean}$. On the opposite side the DPC strategy use more messages but the tendancy is to keep the number of messages under a certain threshold. And for small values of MRAI is also possible for the constant strategy to send more messages than the DPC strategy.

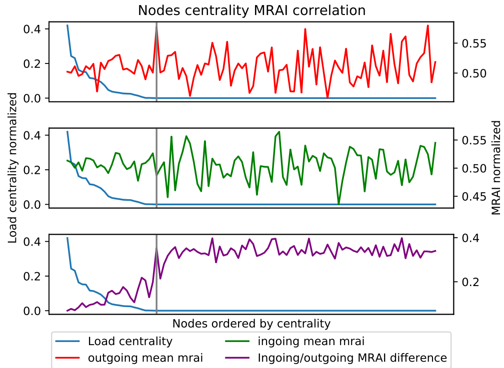
I would like to study more deeply the first part of Figure 18. In particular the experiments with convergence time lower than 20 and the number of messages under 146. We would see what particular MRAI settings those experiments has to produce those good outputs. The results are presented in Figure 20. In those plots we have on the x axis the nodes ordered by centrality. On the first y axis we can see the load centrality value normalized. The blue curve (that is equal on each plot, because the graph is one) represent the centrality of each nodes, thanks to the fact that nodes are ordered by centrality we see this line descending. Is also noticable that the magiority of the nodes have a centrality of zero. Each plot is divided in three sublplots that will help us to understand how MRAI is distributed in the graph. The red line in the first subplot represent the out MRAI mean of each node. The out MRAI of a node is the mean of the MRAI setted on the output links of the node. The second plot contains the input MRAI mean, that is the opposit of the output MRAI mean, so it's the mean of the MRAIs used by the neighbors with the node that we are analyzing. The last subplot contains the absolute difference of the previous two lines. Each point on those lines is the mean of all the graphs that produced results in the reange of our interest.

We can clearly see a correlation between the MRAI and the centrality. It would become even clearer using the second plot that contains also the sandard variation between all the means of the graphs in Figure 20b.

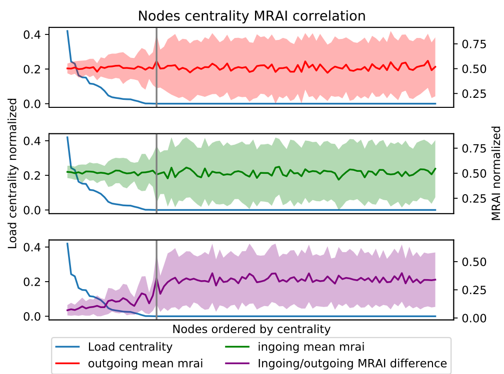
VIII. More signals

I decided to repeat some of the experiments above to see how they react with diferent signals. For now the environment uses only "A" Signal but I would like to see how this has influenced the experiments.

First of all I repeated the experiments with a constant MRAI strategy in the internet like environment, results are available in Figure 21. Like is possible.



(a) Study of the best results in the random experiments



(b) Study of the best result in the random experiments showing the standard deviation

Figure 20: Best random experiments, on the internet like topology, shows the correlation between centrality and the MRAI of the nodes, the gray wertical line represent the first node with centrality of 0 FiXme: **INCORRECT INTERPRETATION, what we see is caused by the RNG, obviously node more central has more input/output edges, with more random values which mean is 0.5 normalized**

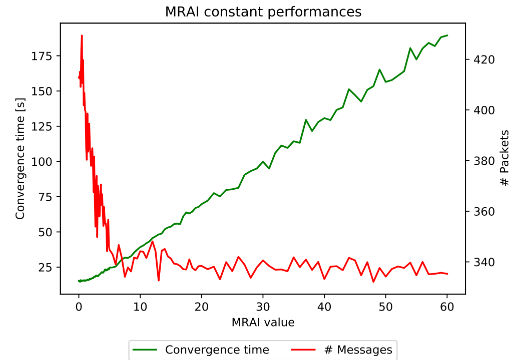
Like is possible to see the curve is more defined, there are less huge spikes in the first part of the plot (with very small MRAIs).

The time line on the other side is still growing linearly, with some more variations but still linearly. The difference between Figs. 21a and 21b is evident and caused by the absence of the implicit withdraw flag.

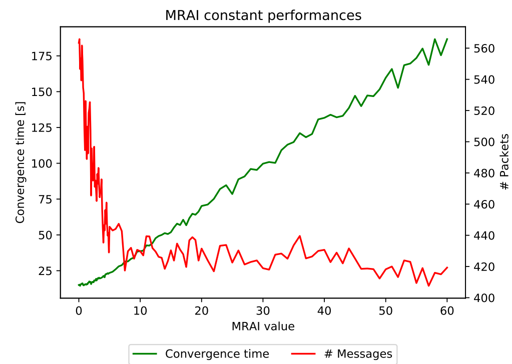
In Figure 22 is possible to see the same plot but with the standard deviation active, knowing that I don't actually indagate more in the possible bug, we can see that the standard deviation is higher in the first path of the plots and then converge to some values.

I have done the same study with the DPC MRAI strategy. Results are available in Figure 23. This time is possible to see a bigg difference between the two stregies. The number of messages sent with the DPC strategy is lower than constant MRAI strategy. This is true also in the case of the implicit withdraw flag deactivated.

The difference is also visible with the standard deviation



(a) constant MRAI in an internet like environment with 100 nodes



(b) constant MRAI in an internet like environemnt with 100 nodes without IW active

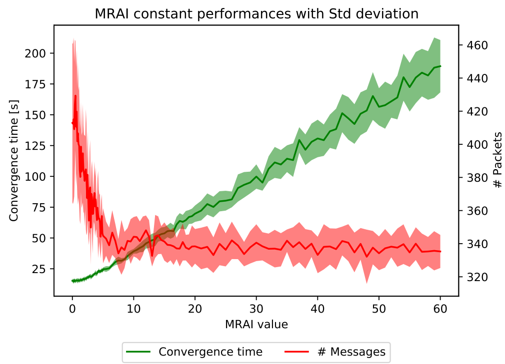
Figure 21: Constant MRAI strategy in an internet like environment of 100 nodes with a source signaling of "AW"

actie, as showed in figure Figure 24, the standard deviation on the convergence time is smaller than the one for the constant MRAI strategy.

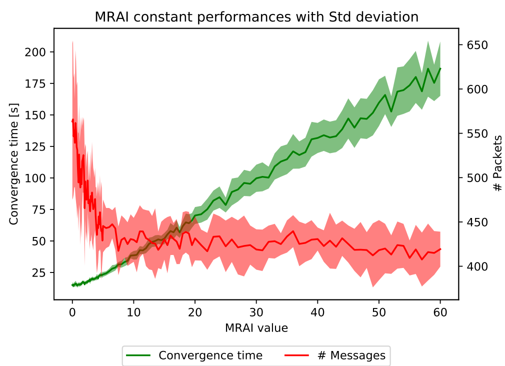
Given this huge variation I decide to compare again the two techniques, as I did in Figure 16. The results are presented in Figure 25 in both plots, time and number of messages, we can see a huge difference between the two techniques.

1) Why?: Why the signaling is so influent? the difference in performances is stunning. Take for example the plot in Figure 16b we can see that the performances are quite equal. This because in my opinion MRAI were not really used apart from some cases. Signaling just an announcement is possible that, apart from some nodes in the network, the number of messages don't differ because they just send the new route to the destination and them are not updated anymore. In the second case, the one presented in Figure 25b, The effects of MRAI are more visible, a node that receives the advertisement and then the withdraw, without having spread the the advertisement allow us to save a lot of further messages. For this reason we see this huge difference in convergence time and number of spreaded messages.

If this happen in the graph internet like of 100 nodes it should happen also in the graph of 1000 nodes, right? I

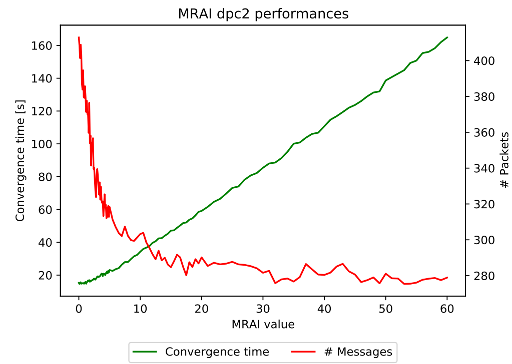


(a) constant MRAI in an internet like environment with 100 nodes, with standard deviation

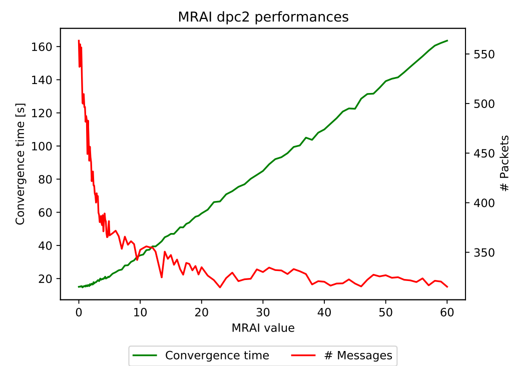


(b) constant MRAI in an internet like environemnt with 100 nodes without IW active, with standard deviation

Figure 22: Constant MRAI strategy in an internet like environment of 100 nodes with a source signaling of "AW", with the standard deviation of the runs visible



(a) DPC MRAI strategy in an internet like environment with 100 nodes



(b) DPC MRAI in an internet like environemnt with 100 nodes without IW active

Figure 23: DPC MRAI strategy in an internet like environment of 100 nodes with a source signaling of "AW"

tried the same experiments in the graph of 1000 but results are not great as the one that we saw in the graph of 100 nodes. This time, I will not show result for the IW environment, because is clear it's trend. In Figure 26 are presented the results. This time the number of experiments is lower, but enough to see the trend, I have done steps of 5 s. This time the difference is not in favour of the DPC strategy. Infact, the number of messages sent is quite similar, the constnat MRAI strategy seems a little bit lower. The difference in terms of convergence time is huge, for the DPC strategy takes more or less 3 times the convergence time of the constant strategy.

The difference in performances is also visible in Figure 27. The standard deviation of the two stregies is similar.

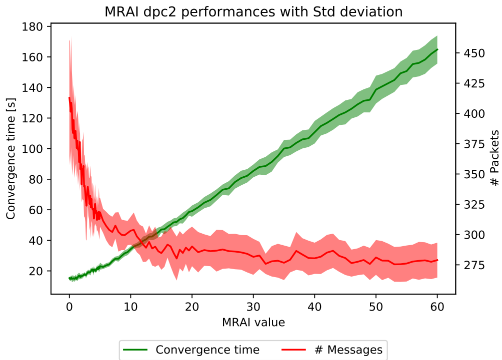
The two dimensions (time and messages) are better compared in Figure 28. Is possible to see that in the case of active IW, the performances in the messages dimension are similar. But as soon as we look to the time dimension we can see a huge gap between the two techniques.

2) Why thid difference?: I think the difference could be caused by the fact that which node generates the signaling is more influent than the signaling itself. I furthermore indagate in this direction, taking different random destinations inside the graph. Once I found the 10 different sources in the graph I then run 10 environments per MRAI strategy, I then compare all the experiments in the same plot. Is also available a plot with the mean of the 10 environments. For each environemnt I run different experiments with different $MRAI_{mean}$ and 10 runs for each $MRAI_{mean}$

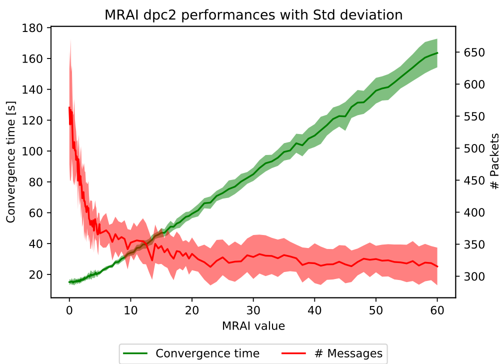
The first try I made was on an internet like graph of 100 nodes. Results are presented in Figure 29. Like is possible to see in Figure 29b the number of messages transmitted is similar between the two strategies, while the convergence time is increasing faster with the DPC techinique.

This in my opinion represent that there is a strong dependance on how good a strategy could in relation of which node is the source of traffic.

I run this type of experiments also in the internet like graph with 1000 nodes, this time with a bigger MRAI step, the trend is also visible, it would be too much time consuming to run the same number of experiments on this bigger graph. Results presented in Figure 30. In those plots, in particular the one in Figure 30b, is possible to see that this time, on average, the DPC technique goes worst than the constant technique on both the time and the number of messages dimension.

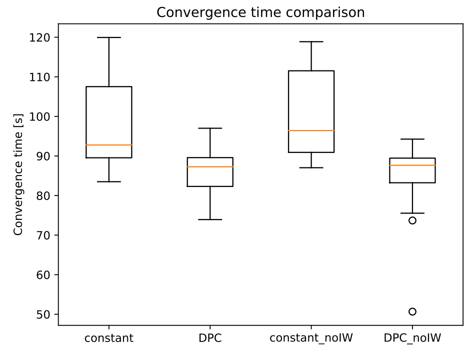


(a) DPC MRAI strategy in an internet like environment with 100 nodes, with standard deviation

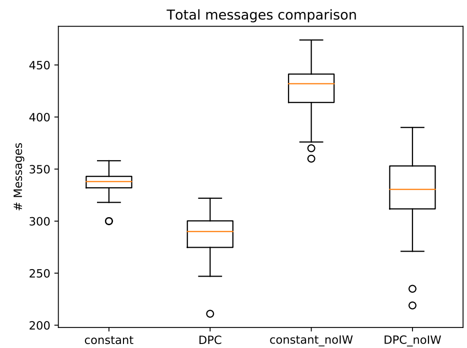


(b) DPC MRAI in an internet like environemnt with 100 nodes without IW active, with standard deviation

Figure 24: DPC MRAI strategy in an internet like environment of 100 nodes with a source signaling of "AW", plots with standard deviation active



(a) Convergence time comparison between different environments



(b) Messages necessary to reach the convergence comparison

Figure 25: Comparison between the DPC MRAI strategy and the constant MRAI strategy, 100 experiments with the same conditions with $MRAI_{mean}$ equals to 30.0. The input signaling is "AW"

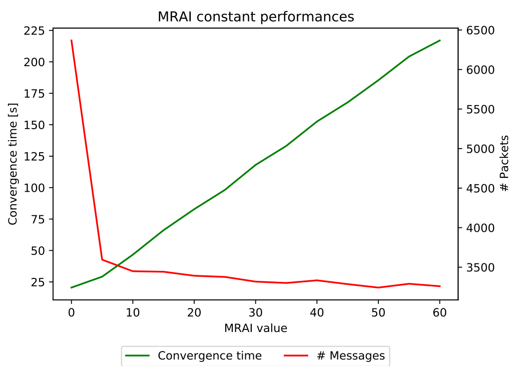
A. *nodes convergence*

One of the other possible field to study on those experiments is the nodes convergence rate per experiment. A node will be considered converged once it's RIB does not variate anymore, new information in input are not going to modify it's knowledge. It can still send messages but once the knowledge is fixed I consider it converged. In each experiments thanks to the outputs of each run we can see on average for each time instant how many nodes has reached the convergence state.

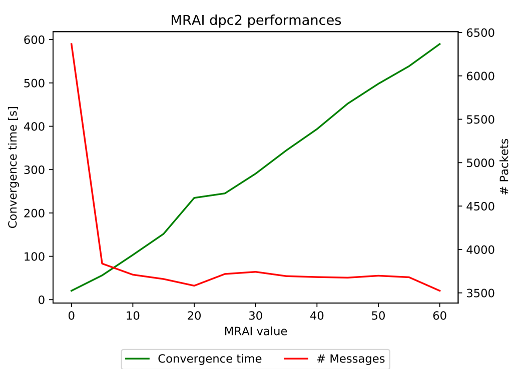
We can then compare different convergence trend with different MRAI strategies MRAI has been fixed to 30 s for those experiments.

The first comparison that I would like to take in consideration is the one between the DPC and constant MRAI stregies in the internet like graph with 100 nodes. The results of this first study are showed in Figure 31 Is possible to notice that, with the DPC strategy the nodes convergens grows faster than the constant streategy, in the constant strategy we have more "steps" that happen to reach the convergence, always around $MRAI_{mean}$.

I did the same experiments with an internet network of 1000 nodes. Results are presented in Figure 32.

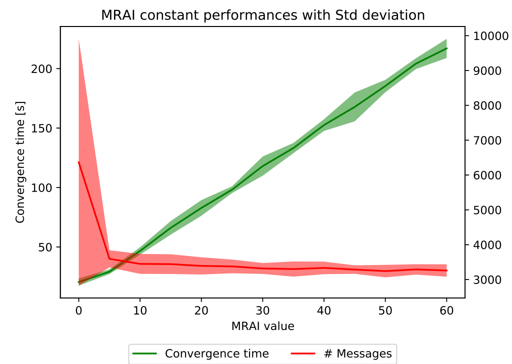


(a) constant MRAI in an internet like environment with 1000 nodes

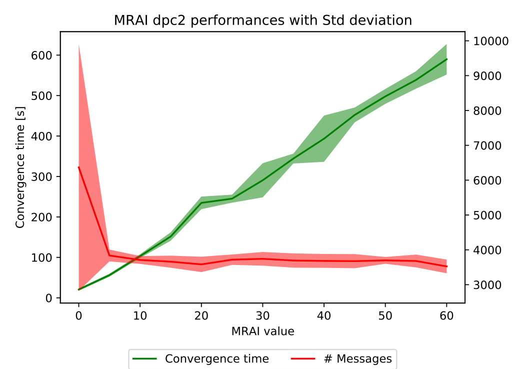


(b) DPC MRAI in an internet like environemnt with 1000

Figure 26: MRAI strategy comparison in an internet like environment of 1000 nodes with a source signaling of "AW" from a random 'C' node

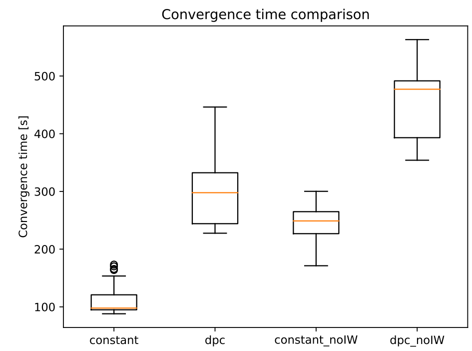


(a) constant MRAI in an internet like environment with 1000 nodes, with standard deviation

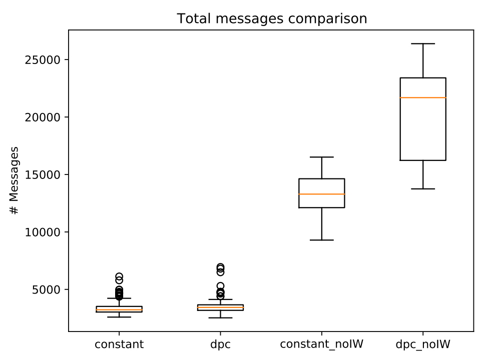


(b) DPC MRAI in an internet like environemnt with 1000, with standard deviation

Figure 27: MRAI strategy comparison in an internet like environment of 1000 nodes with a source signaling of "AW" from a random 'C' node, standard deviation of experiments visible

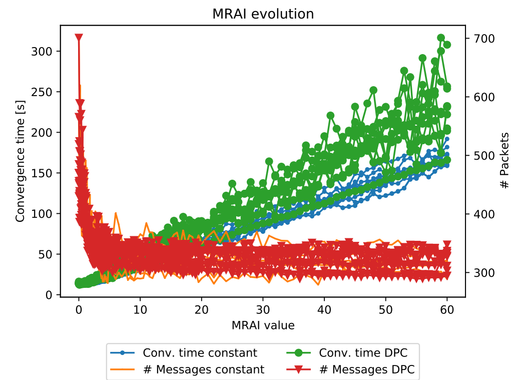


(a) Convergence time comparison between different environments

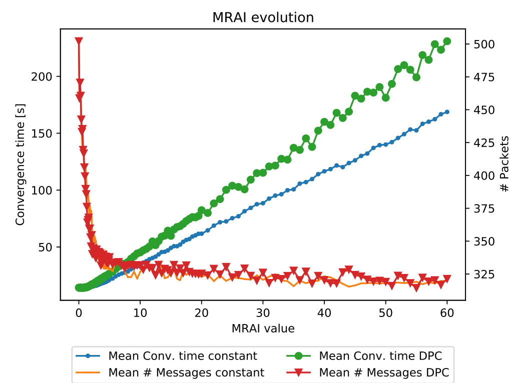


(b) Messages necessary to reach the convergence comparison

Figure 28: Comparison between the DPC MRAI strategy and the constant MRAI strategy, 100 experiments with the same conditions with $MRAI_{mean}$ equals to 30.0. The input signaling is "AW". The graph is an internet like of 1000 nodes

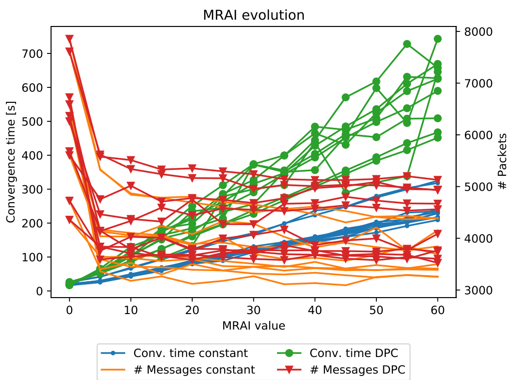


(a) All the experiments run on the graph with different destinations

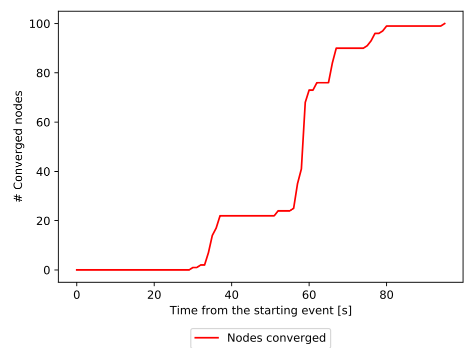


(b) Mean of all the experiments run on the graph with different destinations

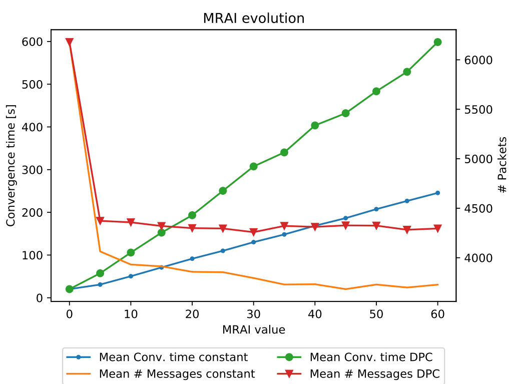
Figure 29: Experiments with random destinations on the internet like graph with 100 nodes, the destination is chosen randomly for each environment



(a) All the experiments run on the internet like graph of 1000 with different destinations

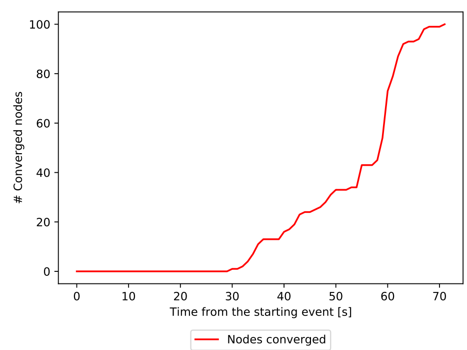


(a) Converged nodes trend with a constant MRAI strategy in the internet like graph of 100 nodes



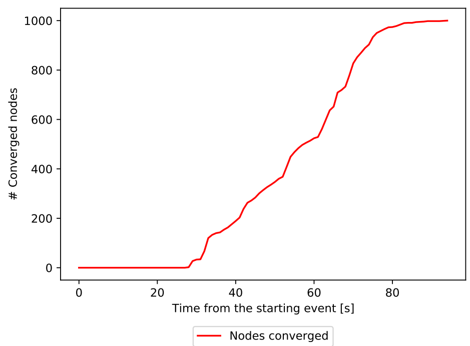
(b) Mean of all the experiments run on the internet like graph of 1000 with different destinations

Figure 30: Experiments with random destinations on the internet like graph with 1000 nodes, the destinations are chosen randomly for each environment

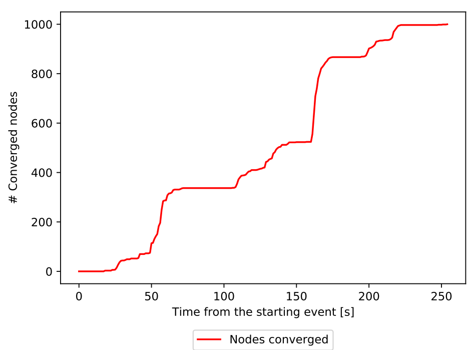


(b) Converged nodes trend with a DPC MRAI strategy in the internet like graph of 100 nodes

Figure 31: Experiments with fixed $MRAI_{mean} = 30s$ in the internet like graph with acronym-next-pages nodes, nodes convergence comparison of differen MRAI techniques FiXme: The two plots are not easily comparable on eye



(a) Converged nodes trend with a constant MRAI strategy in the internet like graph of 1000 nodes



(b) Converged nodes trend with a DPC MRAI strategy in the internet like graph of 1000 nodes

Figure 32: Experiments with fixed $MRAI_{mean} = 30s$ in the internet like graph with acronym-next-pages nodes, nodes convergence comparison of differen MRAI techniques FiXme: The two plots are not easily comparable on eye

IX. More MRAI strategies

In this section I would like to study more MRAI strategies that in my opinion can affect the numeber of messages and the convergence time.

The MRAI stregies that I compared are the following:

- ***Constant***: MRAI is equal for each edge in the graph;
- ***DPC***: MRAI is setted, knowing the source node accordingly to Equation (3); Speed up the comunication with the core, slow down the spreading after the core
- ***Reverse_dpc***: MRAI is setted using a function like the DPC strategy, but using the first and last equation switched, fomula available in Equation (4) for a quick look; Slow down the spreading while reaching the core, then speed up while reaching the rest of the network;
- ***Centrality***: Every edge MRAI is setted accordingly to the normalization of the centrality, $MRAI_{ij} = \Delta(i) MRAI_{mean}$; Central nodes have an higher timer;
- ***Reverse_centrality***: the reverse of the prevous one, $MRAI_{ij} = |1 - \Delta(i)| MRAI_{mean}$; Central nodes have a lower timer;
- ***Banded_centrality***: the same as centrality but with the centrality rounded to the first decimal;
- ***Reverse_banded_centrality***: like the revere_centrality but with the centrality rounded to the first decimal;

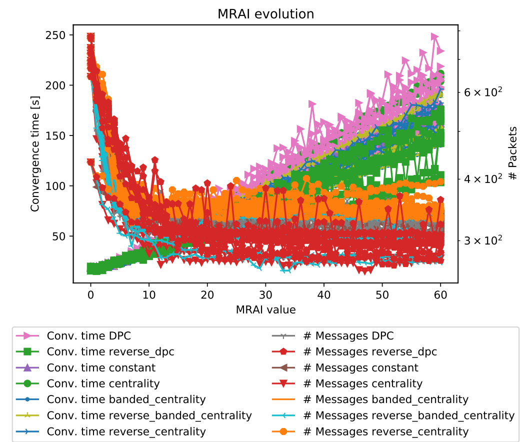
$$T_{ij} = \begin{cases} \frac{T(1-\Delta(i))}{2} + \frac{T}{2} & \forall i \in \mathcal{V}^{\mathcal{G}_{\mathcal{D}}} \\ \frac{T}{2} & \forall i \in \mathcal{V}^{\mathcal{G}_{\mathcal{T}}} \\ \frac{T}{2}\Delta(i) & \forall i \in \mathcal{V}^{\mathcal{G}_{\mathcal{A}}} \end{cases} \tag{4}$$

Using an internet like graph of 100 node I have done for each MRAI strategy different experiments, one for each possible $MRAI_{mean}$ value in $[0, 60]$. For each single experiment has been run 10 different simulations. I then repeated for each MRAI strategy the same sequence of experiments for 10 different destinations in the network.

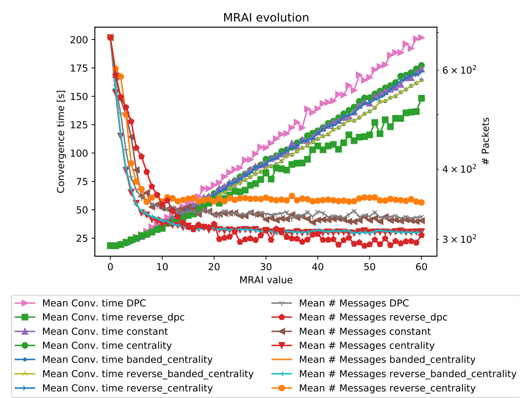
In Figure 33a are available all the 10 lines for each different destination evolution for each MRAI strategy. This graph is quite incomprehensible, so in Figure 33b is available for each MRAI strategy the average of the 10 destination experiments.

Please notice that in both plots in Figure 33 the second Y axis is in log scale and it represent the number of messages necessary globally in the network to reach the convergence state. The first Y axis instead, it refers to the convergence time in seconds that the network required to converge.

In Figure 33b is possible to notice that, on average (remember that those data are highly dependent by the position of the source node), the worst technique in terms of convergence time is the *DPC* one, while in terms of messages necessary to reach the convergence is the *Reverse_centrality*. While, mostly of the techniques goes as the constant one in terms of convergence time. On the opposit side, one techinique distinguished itself from the others, it's the *reverse_dpc*. The *reverse_dpc* is the best one in terms of convergence time and also number of messages necessary to reach the convergence.



(a) Multiple random destinations on more MRAI strategies, on an internet like graph of 100 nodes



(b) AVerage of all the random destination runs by MRAI strategy, on an internet like graph of 100 nodes

Figure 33: Experiments with random destinations on the internet like graph with 100 nodes, the destinations are chosen randomly for each environment. More MRAI strategies analyzed

Previous results were obtained on an internet graph of 100 nodes, we should see on a graph of 1000 nodes if those results are confirmed.

I have done the same experiment setup (10 different signal sources) this time with less MRAI strategies, I was interested only in the worst one (*DPC*) the average one (*constant*) and the best one (*Reverse_dpc*). I had to reduce also the number of $MRAI_{mean}$ values for time reasons, this time the step was of $10\,\text{s}$ in teh range $[0, 60]$.

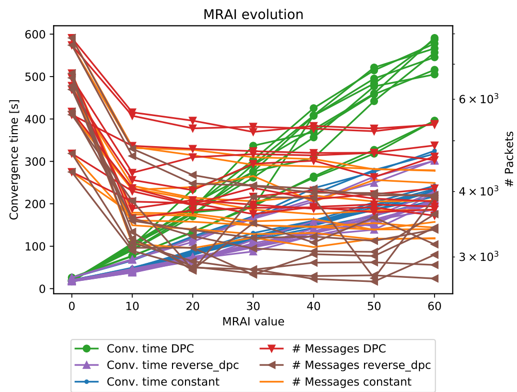
Like before results are available with the same plot style in Figure 34 Is possible to notice istantly in the average plot in Figure 34b that there is a huge difference in those techniques, the *reverse_dpc* is the best one in terms of messages and also convergence time.

A. Why reverse goes better?

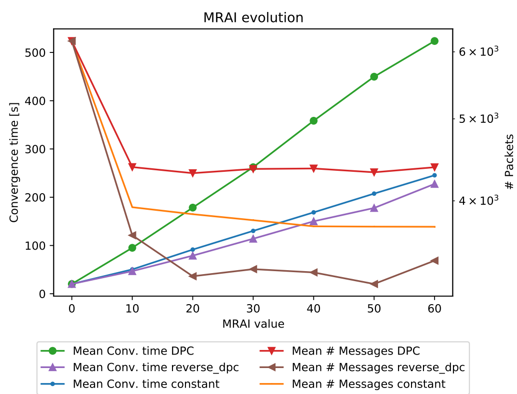
I would like to understand why the reverse of the DPC technique goes better than the original one.

Hipothesis:

If the information reaches more slowly the center of the network



(a) Multiple random destinations on more MRAI strategies, on an internet like graph of 1000 nodes



(b) AVerage of all the random destination runs by MRAI strategy, on an internet like graph of 1000 nodes

Figure 34: Experiments with random destinations on the internet like graph with 1000 nodes, the destinations are chosen randomly for each environment. More MRAI strategies analyzed

so is possible that there has been a sequence of constructive timers in a way that the information spreaded by a central node doesn't need future correction. In this way far away nodes only receives a correct information in a fast way once the central nodes are converged. The information take more time to reach the center of the network but it's more probably that it's correct and doesn't neeed other correction, so nodes can converge with less messages.

To confirm my Hipothesis I need to study a single network experiment for both the interesting MRAI strategy that I found, the *dpc* strategy and the *Reverse_dpc* one. I have chosen the experiment with destination id 0 and $MRAI_{mean} = 30$ in the graph of 1000 nodes.

I then separated the nodes in groups, each group represent the distance in terms of hops from the signal source. So for example in group 3 there are nodes which best path contains three edges to reach the destiantion.

For each group I then evaluated the two classic methrics that I used up to now, the convergence time on average in the group and the number of messages necesary on average to reach the convergence.

I have then correlated those information with the centrality of the nodes in the group.

In Figures 35 and 37 are contained all those information. Those plots are quite complicated... On the X axis are represent the nodes in the network, ordered by group affiliation and then inside each group nodes are ordered by centrality. The orange vertical lines delimit groups, while the blue line represent the centrality, notice that the first Y axis on the left is used for the centrality metric and it's in log scale. The average centrality of a group is represented by the blue horizontal dotted line.

The first thing that we can notice looking only to the nodes in groups and the centrality is that the magiority of the nodess are far away from the destination source, Two groups occupy the magiority of the plot. We can also notice that the centrality peaks are reached in one of nearest groups whith less nodes of the other two.

Then if we look to Fig. 35a is possible to correlate the convergence time to the groups. The red horizontal dotted line represent the average convergence time of the group. While, the green line represent each node convergence time. We can notice that in every group there is a huge variation in the convergence time. And the most important thing to notice in my opinion is that one of the first groups, with the highest centrality it takes on average more time to converge than the other two groups that are the majority of the network.

The more central nodes are unconverged up to the end of the experiment on average.

The second plot Figure 35b correlate the number of messages required to converge with the group position of the nodes and the centrality. The ping horizontal dotted line represent the average on messages required to converge. That central nodes require more messages on average to reach the convergence in my opinion is correct, but the huge variance in the two last groups, with a lot o spikes represent that nodes far away from the destination receive a lot of uncorrect paths.

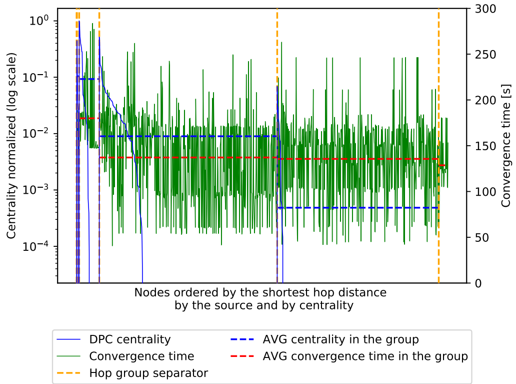
In Figure 36 are represented the average trends of the different groups. Each point of the lines is the average of a group, with lose the concept of how many nodes are in a group but it's more easy to look only on average how a specific group goes during the experiment.

Is possible to notice in Figure 36a that the nodes with the highest centrality on average requires also the highest time to converge. In Figure 36b the same phenomenon is present.

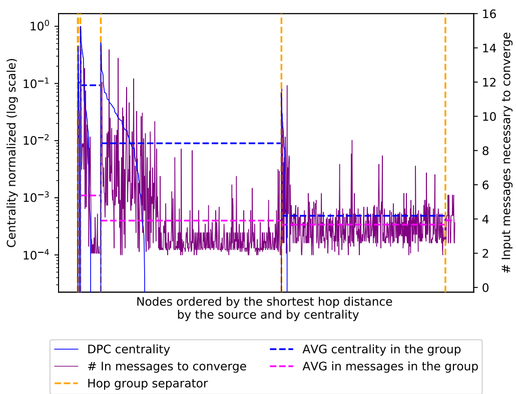
With the DPC MRAI strategy the bottleneck is in the central nodes. What happens in the *reverse_dpc* technique?

The same plots are available for this technique in Figures 37 and 38. Obviously the centrality and the group separation is the same, what change is the time necessary to converge and less variance in the number of mesages required. Is clearly visible in Figure 37b that the last group, the farest from the source has a lot less variation, and that in the second last group there is a spike of messages only in the nodes that have a higher centrality.

Is important to notice a huge difference between Figure 38a and Figure 36a. In the *DPC* case the central nodes require a higher time to converge, in the other case are the farest



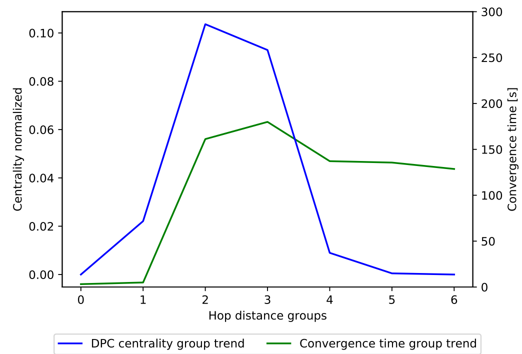
(a) Convergence time VS Nodes centrality/distance from the source. Single experiment (10 runs) on a single destination, graph Internet like with 1000 nodes, $MRAI_{mean}$ of 30 s, MRAI strategy DPC. Nodes divided in groups by the hop distance from the source and then each group is ordered by centrality.



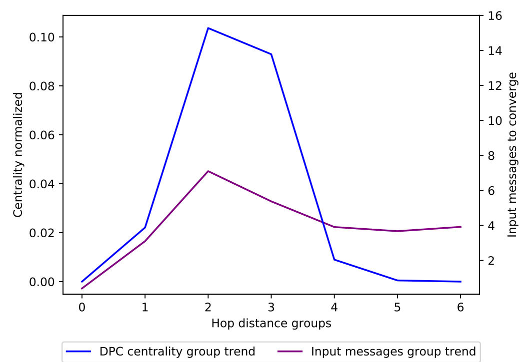
(b) Number of input messages required to converge VS Nodes centrality/distance from the source. Single experiment (10 runs) on a single destination, graph Internet like with 1000 nodes, $MRAI_{mean}$ of 30 s, MRAI strategy DPC. Nodes divided in groups by the hop distance from the source and then each group is ordered by centrality.

Figure 35: Correlation between centrality and distance from the source and the DPC MRAI strategy. Experiment with one random destination on the internet like graph with 1000 nodes, $MRAI_{mean}$ of 30 s and DPC as MRAI strategy

nodes that converge slowly. This is interpretable as the central nodes receive a correct information faster than the other farest nodes. Instead, in terms of messages, farest nodes with the *reverse_dpc* technique nodes receive less messages on average, almost the half respect to the *DPC* technique. This means that they receive more likely correct information than paths that will be then rewritten.

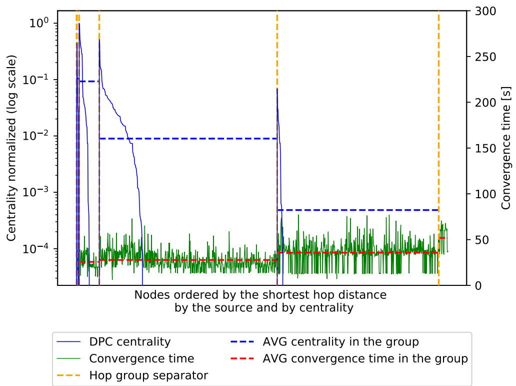


(a) Average groups values for centrality and convergence time.

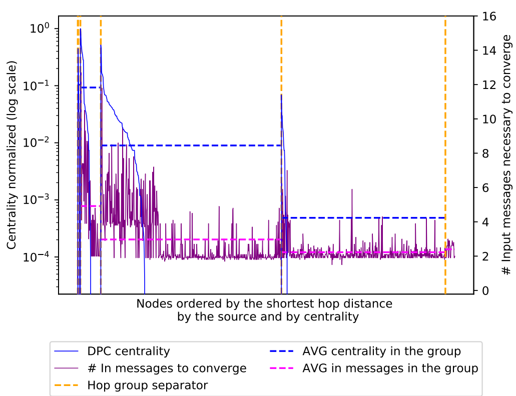


(b) Average groups values for centrality and messages necessary to converge.

Figure 36: Correlation between centrality and distance from the source and the DPC MRAI strategy. Simplified group trend view Experiment with one random destination on the internet like graph with 1000 nodes, $MRAI_{mean}$ of 30 s and DPC as MRAI strategy

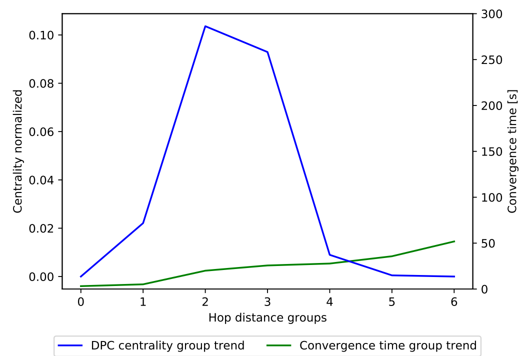


(a) Convergence time VS Nodes centrality/distance from the source. Single experiment on a single destination, graph Internet like with 1000 nodes, $MRAI_{mean}$ of 30 s, MRAI strategy reverse_dpc. Nodes divided in groups by the hop distance from the source and then each group is ordered by centrality.

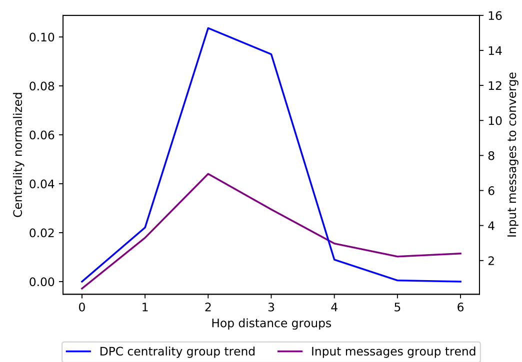


(b) Number of messages required to converge VS Nodes centrality/distance from the source. Single experiment on a single destination, graph Internet like with 1000 nodes, $MRAI_{mean}$ of 30 s, MRAI strategy reverse_dpc. Nodes divided in groups by the hop distance from the source and then each group is ordered by centrality.

Figure 37: Correlation between centrality and distance from the source and the DPC MRAI strategy. Experiment with one random destination on the internet like graph with 1000 nodes, $MRAI_{mean}$ of 30 s and reverse_dpc as MRAI strategy



(a) Average groups values for centrality and convergence time.



(b) Average groups values for centrality and messages necessary to converge.

Figure 38: Correlation between centrality and distance from the source and the DPC MRAI strategy. Experiment with one random destination on the internet like graph with 1000 nodes, $MRAI_{mean}$ of 30 s and reverse_dpc as MRAI strategy

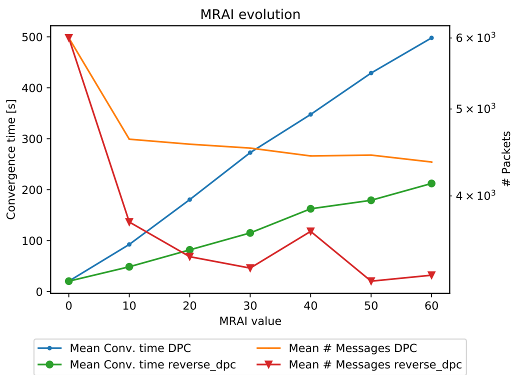


Figure 39: Average messages and convergence time, graph of 1000 nodes, 12 experiments, 3 random destination for each level

X. Hierarchical level study

We know that the position of the signaling node has a huge impact in the convergence time and the number of messages transmitted. So now is time to study this position and how it affects the performances.

My approach to study the position influence is to proced by levels. We saw in Figure 2b that internet like networks have a hierarchical structure, so we can expolit this structure to study differnt levels correlations.

I took an internet graph of 1000 nodes and two MRAI techniques to compare, the *DPC* and *Reverse_dpc* technique.

This graph had 4 hierarchical level from the central clique of nodes So i get 3 nodes of type C from each level.

I have then run all the experiments like before, 12 experiments for each MRAI strategy. In Figure 39 is possible to see a general plot of on average how those experiments went. Like before the best technique was the *reversse_dpc*.

Is possible to look on average how each level went in Figure 40 Line colors correspond to the colors in Figure 39. It's really small and if printend you wouldn't see anything, but hankfully on a pc is possible to zoom and see the trends.

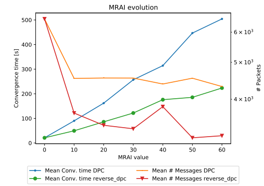
Now that we saw that even on different levels the *reverse_dpc* technique is better than the DPC one I would like to study the group trend like we did in Section IX-A.

I will not use the compleate plots of all the nodes because them are quite incomphrehensible for easy comparison. Instead, I'll use the group trends plots to compare some of the levels. I took the experiments that have $MRAI_{mean} = 30s$ to plots in Figures 41 and 42. I didn't insert the plots of the level 2 because are really similar to the level 1.

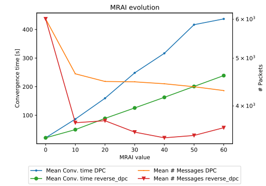
In Figure 41 is possible to compare the trends of the groups for the two different techniques. The groups are equal between the two techniques for each source node because the graph is the same for each MRAI technique. In the same way is equal also the centrality, infact the blue line is equal in the plots in couples.

The difference to compare is in green line that represents the convergence time.

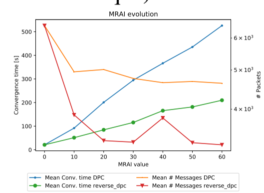
One really interesting level is the firt one. The centrality is really high in the first group near the source of the signal, taht



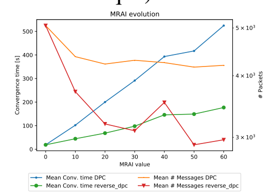
(a) Level 1 (source at 1 hop from the central clique)



(b) Level 2 (source at 2 hops from the central clique)



(c) Level 3 (source at 3 hops from the central clique)



(d) Level 4 (source at 4 hops from the central clique)

Figure 40: Different levels average trend of messages sent and convergence time for different MRAI techniques and different $MRAI_{mean}$ Graph internt like of 1000 nodes

because we are at 1 hop from the clique in the center of the node, and from that node we can reach a lot of other nodes with just the first hop. In both plots Figures 41a and 41b we notice that the central nodes converges really fast but the other part of the network is a compleatly different story. It seems tath with the *DPC* technique the next parts of the network take a lot of MRAI cicles to get the right information, that's not true for the *Reverse_dpc*.

On the other plots we can see similar trends, the *DPC* technique seems to be sort of logaritmic, while the *Reverse_dpc* technique grows linearly but really slowly.

Some reasonings could be also done for the messaging trends in Figure 42. In the first two plots (level 1) is possible to see that the farest nodes require more messages that the closer nodes. Thats because they receive wrong iformation that needs to be corrected by other messages. This don't happen in the other levels, that because the nodes in the first spreading part have a function of filter, central nodes should receive more messages than the other but if the magiority of the messages are correct then them will spread a correct information to the farest nodes. This will provoke less messages in the farest part of the network.

Is possible to observe a compleate comparison of all the levels in one plot in Figure 43.

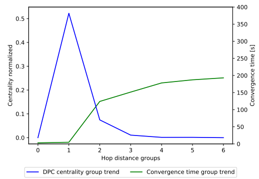
References

[1] A. Fabrikant, U. Syed, and J. Rexford, "There's something about MRAI: Timing diversity can exponentially worsen BGP convergence," in *30th IEEE Int. Conf. on Computer Communications (INFOCOM 2011)*, Shanghai, China, Apr. 2011.

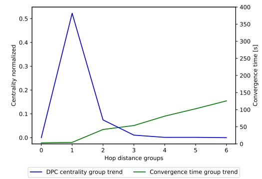
[2] A. Elmokashfi, A. Kvalbein, and C. Dovrolis, "On the Scalability of BGP: The Role of Topology Growth," *IEEE Jou. on Selected Areas in Communications (JSAC)*, vol. 28, no. 8, pp. 1250–1261, 10 2010.

[3] T. G. Griffin and B. J. Premore, "An experimental analysis of bgp convergence time," in *Proceedings Ninth International Conference on Network Protocols. ICNP 2001*. IEEE, 2001, pp. 53–61.

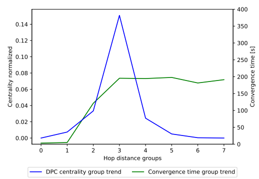
[4] M. Milani, M. Nesler, M. Segata, L. Baldesi, L. Maccari, and R. L. Cigno, "Improving bgp convergence with fed4fire+ experiments," in *IEEE INFOCOM 2020-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*. IEEE, 2020, pp. 816–823.



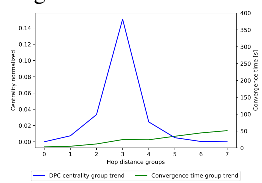
(a) Level 1 *DPC* strategy convergence time trend



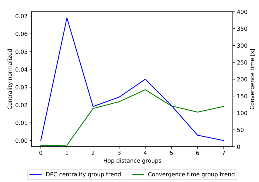
(b) Level 1 *Reverse_dpc* strategy, convergence time trend



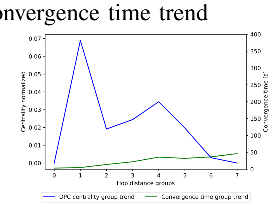
(c) Level 3 *DPC* strategy convergence time trend



(d) Level 3 *Reverse_dpc* strategy, convergence time trend



(e) Level 4 *DPC* strategy convergence time trend



(f) Level 4 *Reverse_dpc* strategy, convergence time trend

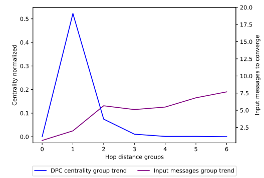
Figure 41: Different MRAI strategies convergence time comparison in function of the hop group from the source node. Graph internet like of 1000 nodes. Comparison taken at $MRAI_{mean} = 30s$

[5] U. Brandes, "On Variants of Shortest-Path Betweenness Centrality and their Generic Computation," *Social Networks*, vol. 30, no. 2, pp. 136–145, May 2008.

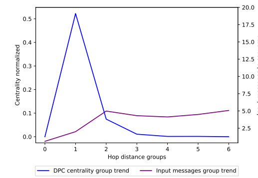
[6] L. Maccari and R. Lo Cigno, "Improving Routing Convergence With Centrality: Theory and Implementation of Pop-Routing," *IEEE/ACM Trans. on Networking*, vol. 26, no. 5, pp. 2216–2229, Oct. 2018.

[7] L. Maccari, L. Ghiro, A. Guerrieri, A. Montresor, and R. Lo Cigno, "On the Distributed Computation of Load Centrality and Its Application to DV Routing," in *37th IEEE Int. Conf. on Computer Communications (INFOCOM)*, Honolulu, HI, USA, Apr. 2018, pp. 2582–2590.

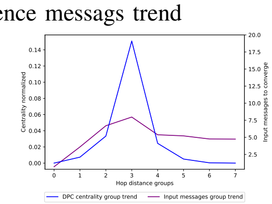
[8] C. Labovitz, A. Ahuja, A. Bose, and F. Jahanian, "Delayed internet routing convergence," *ACM SIGCOMM Computer Communication Review*, vol. 30, no. 4, pp. 175–187, 2000.



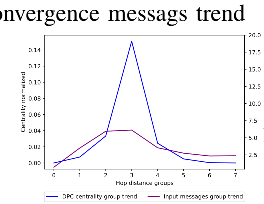
(a) Level 1 *DPC* strategy convergence messags trend



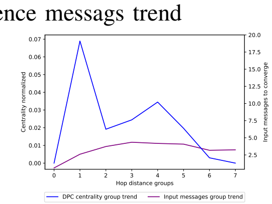
(b) Level 1 *Reverse_dpc* strategy, convergence messags trend



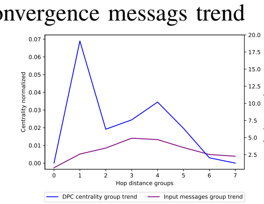
(c) Level 3 *DPC* strategy convergence messags trend



(d) Level 3 *Reverse_dpc* strategy, convergence messags trend

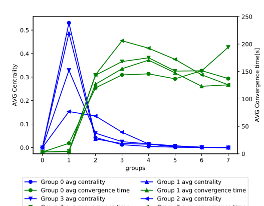


(e) Level 4 *DPC* strategy convergence messags trend

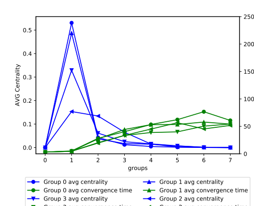


(f) Level 4 *Reverse_dpc* strategy, convergence messags trend

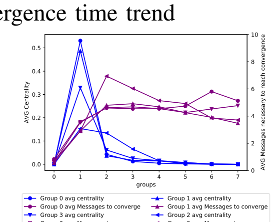
Figure 42: Different MRAI strategies, in messages necessary to converge comparison in function of the hop group from the source node. Graph internet like of 1000 nodes. Comparison taken at $MRAI_{mean} = 30s$



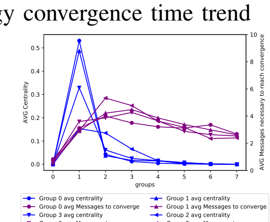
(a) All levels, *DPC* strategy convergence time trend



(b) All levels, *Reverse_dpc* strategy convergence time trend



(c) All levels, *DPC* strategy convergence messags trend



(d) All levels, *Reverse_dpc* strategy, convergence messags trend

Figure 43: Different MRAI strategies, comulative plot for all the levels trends in function of the hop group from the source node. Graph internet like of 1000 nodes. Comparison taken at $MRAI_{mean} = 30s$