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# SIMULATING THE EFFECT OF DEGRADED WIRELESS COMMUNICATIONS ON EMERGENT BEHAVIOR

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## ABSTRACT

Most swarming algorithms require individual nodes to know the locations of their nearest-neighbor peers. Existing work assumes that this information is abundant and readily available, however, when wireless communications are used for data exchange, issues regarding dissemination arise. These include partial or complete data loss and an increased latency, significantly affecting the quality of the delivered service. In this paper, we show through extensive experimental analysis that swarm intelligent algorithms are vulnerable to degraded communication. To show how communication is affected in a contested environment, we introduce a local interaction statistic metric to capture emergence. Our analysis using agent-based simulation characterizes the decay of inherent emergence and swarm efficiency with increasing data loss and delay.

## 1 INTRODUCTION

First introduced in the context of cellular robotics, swarm-intelligence has been viewed as non-trivial intelligent behavior exhibited in unpredictable systems capable of producing order (Beni and Wang 1993). This 'robot system intelligence' could be produced by a collection of autonomous, non-synchronized, non-intelligent robots; ultimately achieving a global task. This process is now known as emergent behavior, and while the definition of this term has been hotly debated (Boschetti, Prokopenko, Macreadie, and Grisogono 2005, Johnson 2006), it is used here simply to refer to the process that produces the global property that we are interested in exploiting.

Swarming-based systems can be found throughout the natural world and extensive research has analyzed the various emergent properties shown by such systems (Bonabeau, Dorigo, and Theraulaz 1999, Floreano and Mattiussi 2008). This includes the flocking behavior of birds and fish (Reynolds 1987, Olfati-Saber 2006), the self-organizing nature of ant colonies (Dorigo, Bonabeau, and Theraulaz 2000) and the intelligent foraging of honey bees (Karaboga and Basturk 2007). Swarming-based systems have also began to be used for the intelligent placement of platforms for uses such as surveillance and target tracking, many of which exploit the simple rules of Reynolds' Boids model (Semnani and Basir 2015, Miao, Khamis, and Kamel 2010, Ganganath, Cheng, and Tse 2015).

Swarming algorithms are appealing for resilient communications as their inherent robustness and low-overhead control schemes makes them suitable to both physically and electromagnetically harsh environments. Several works have examined a type of Boids-like algorithm where swarm members consider 'user' nodes to be part of the swarm (Konak, Buchert, and Juro 2013, Hunjet 2015). User nodes however are allowed to move with their own purpose, forcing the non-user swarm members to adapt the topology. These algorithms however, are considered in the absence of traffic and communications models. If wireless communications are to be used to disseminate the information required for swarming, then studies must include them. A natural-world analogy would be a flock of birds who fly into clouds. In this instance, a critical question is how much visibility is required for the birds to continue to produce the emergent flocking behavior?

In this paper, we propose the use of agent-based simulation that includes wireless propagation and communication models to study the relationship between the quality of the environment that facilitates communication and the emergent behavior exhibited by the swarm. The main contributions of this work are:

- The in-depth analysis of the relationship between the issues pertaining to wireless communications and the breakdown of emergent behavior; and
- The introduction of an autocorrelation function as a tool for the indication of emergence within the state change time-series of individual agents; and
- An extensive experimental analysis highlighting the relationship between the quality of wireless communication and emergent behavior.

## 2 RELATED WORK

We analyze in this section existing work in communication-based algorithms using swarming or similar techniques. Existing literature provides several examples of communications-based algorithms. For example, in (Konak, Buchert, and Juro 2013), the authors use flocking to create a mesh of communications nodes to provide connectivity to user nodes moving according to a random waypoint model. The Boids model is not the only one in which the emergent behavior creates a mesh-like structure. The algorithm in (Wang, Cao, and Porta 2004), inspired by electromagnetic forces, repels peer nodes based on node separation distance to maximize area coverage in a wireless sensor network. (Heo and Varshney 2005) use a similar mechanism, this time motivated by the movement of particles that follow Coulomb's law for charged particles. Even simpler, the author in (Hunjet 2015) proposes to use simple attraction and repulsion rules on an agent's nearest neighbor based on communication range to autonomously control extra network resources to create a well-connected topology. For topologically sparse networks, we have previously explored a data ferrying approach to communications through pheromone-based, swarm coordination (Fraser and Hunjet 2016).

Until recently, the cost and complexity of implementing swarming algorithms in real-life systems has been prohibitive. However, the physical implementation of swarming-based systems is fast becoming a reality. In late 2015, the U.S. Office of Naval Research demonstrated a swarm of 30 autonomous UAVs performing maneuvers that simulated an aerial bombardment of ground targets (Smalley 2015). Only a year later, the Live-Fly program from the U.S. Naval Postgraduate School, conducted the autonomous launch, flight and landing of 50 UAVs (Chung et al. 2016). Later that year, the China Electronics Technology Group Corporation demonstrated the take-off and formation flight of 67 fixed wing UAVs. More recently, the U.S. Department of Defense's Strategic Capabilities Office showed several autonomous missions carried out by 103 micro-UAVs after being launched from three fighter aircraft (US Department of Defense 2017).These developments represent a three-fold increase in swarm numbers over 18 months. As numbers continue to grow, more pressure will be placed on the communications operating within the swarm, particularly if nodes generate their own data, video streams for example, in addition to what is required for swarm operation.

One of the largest swarm demonstrations to date had 1000 miniaturized robots participating in self-assembly (Rubenstein, Cornejo, and Nagpal 2014). Robots communicated via infrared radio reflecting off a table top. Infrared communications are inherently short-range and free-space optics in general are highly directional, reducing possible interference. This paper however, considers off-the-shelf radios with omni-directional (isotropic in two-dimensions) antennas where each swarm member is considered to be a communications node. Nodes then constitute (and communicate via) a Mobile Ad-hoc NETwork (MANET).

MANETs, comprised of individual nodes that are free to move, communicate directly with their peers via a wireless medium (Toh 2002). The network does not have a single controller to manage network traffic flows but rather all nodes act as routers, forwarding on information that is addressed to other network nodes.

Fixed infrastructure is not required making them suitable to environments where infrastructure does not exist, or has been destroyed. Wireless communication networks, such as MANETs, can be degraded through a variety of processes including path-loss, multi-path interference, jamming, contention and congestion. As noted by Chan, no emergence can arise in a swarm without interaction from its parts (Chan 2011). Consequently, if interaction is hindered by communications issues, any extant emergent behavior is likely to break down, decreasing the effectiveness of the swarm. This study therefore analyzes the effect of common (wireless) communications problems on correct swarm operation through agent-based simulation.

## 3 THE ATTRACTION-REPULSION ALGORITHM

Our study analyses the attraction and repulsion algorithm (Hunjet 2015). This algorithm produces a mesh-building emergent property where all agents (nodes) spread out into a regular rhomboid grid with agents contained within a single connected component in a graph sense. It is of interest for the use of providing resilient communications, as the mesh structure is suitable for this purpose. The pseudocode for the algorithm is as follows:

```
initializeAgents();
while isRunning do
    broadCastAgentPosition();
    nearestNeighbourAgentDistance ← findNearestNeighbourAgentDistance();
    if nearestNeighbourAgentDistance not null then
        if nearestNeighbourAgentDistance < minimumDistance then
            moveAway();
        else if nearestNeighbourAgentDistance > maximumDistance then
            moveTowards();
    end
end
```

Algorithm 1. The attraction-repulsion algorithm.

At each step of the algorithm, each agent finds their nearest-neighbor and will either move away or towards it, or stay put depending on the distance to the neighbor.

### 3.1 Metrics

As real-life, physical implementations of swarming systems become feasible, it is of paramount importance that the system is evaluated to determine its suitability for purpose, if the desired emergent property materializes, and if this emergent property has any undesirable side-effects. To address this challenge, metrics for monitoring the performance of a swarm are needed. As the swarm is being built for a particular purpose or desired emergent property, some of these metrics will be application domain specific. However, existing work has introduced several generic metrics whose values are good indicators that emergent behavior exists within the swarm. In this study, we employ both *purpose-driven metrics* and *emergent behavior metrics* to analyze the suitability of the attraction-repulsion algorithm and its physical implementation for data dissemination. Purpose-driven metrics describe *how* well the swarm is performing, while emergent behavior metrics give an indication as to *why*. Our hypothesis is that a swarm will not perform well for a given task if its emergence is poor, however, high emergence does not necessarily mean the swarm will perform well for a certain task. We discuss these metrics below.

### 3.2 Purpose-driven Metrics

The purpose of the attraction-repulsion algorithm is to have swarm members form a highly-connected topology with a large coverage area. We propose the following purpose-driven metrics:

1. *Number of connected components* - The number of isolated subgraphs in the supergraph.
2. *Number of articulation points* - Also known as a cut-vertex, an articulation point is a vertex which, if removed (or cut), would cause the graph to become disconnected.
3. *Area coverage* -The coverage of a node is defined here as the area of a circle with radius R=100 and origin at the nodes location. The topology coverage is then the sum of the circular areas over all nodes with overlapping regions counted only once.

These metrics focus on the physical layer topology but other candidate, purpose-driven metrics could be drawn from the communications literature, for example, traffic throughput and network capacity.

### 3.3 Emergent Behavior Metrics

The statistics of interaction between agents as a measure of emergent behavior was examined in (Chan 2011) and has subsequently driven more complex techniques of identifying emergent behavior (Szabo, Teo, and Chengleput 2014). In this paper we consider effective, directional interactions. They are effective in that an interaction between agents induces an outcome and leads to a state change. They are also directional in that the interaction is initiated by one of the two interacting agents (Chan 2011).

In the attraction-repulsion model, given a set of agents $A$, a state change for agent $i \in A$ does not occur when either:

1. Its neighbor set $N_i(t)$ is empty and therefore cannot position itself relative to another agent.
2. The distance $d_{i,t}^{\min}$ of agent $i$, at time $t \in \mathbb{Z}$, $t > 0$, to its nearest-neighbor is such that $R_{\min} < d_{i,t}^{\min} < R_{\max}$ where $R_{\min}$ and $R_{\max}$ are the minimum and maximum distances respectively within which represent the steady state position for the agent.

In all other cases, an effective interaction occurs. An indicator function is defined in (Chan 2011) for an interaction, which in this case, takes the form

$$\delta_{i,t} = \begin{cases} 0, & R_{\min} < d_{i,t}^{\min} < R_{\max} \text{ or } |N_i(t)| = 0, \\ 1, & \text{otherwise} \end{cases}$$

where $\delta_{i,t}$ is the indicator function of agent $i$ at time $t$. The following time-series statistics are considered:

- The total state change at time $t$, $I_t = \sum_{\forall i} \delta_{i,t}$; and
- The total cumulative state change at time $t$, $Z_t = \sum_{\forall i} X_{i,t}$ where $X_{i,t} = \sum_{l=1\dots t} \delta_{i,l}$.

We also capture the time-series of state changes of each agent, $x_i = \delta_{it},\ 1\dots T$ and introduce the use of the autocorrelation function (ACF) on $x_i$ as an emergence indicator. The ACF computes the similarity between observations as a function of the time lag between them and can be used to detect non-randomness in data (Box, Jenkins, Reinsel, and Ljung 2015). The use of the ACF comes with two assumptions:

1. The next state of an agent is correlated with the current state (in some unknown way) if emergent behavior exists; and similarly
2. Emergent behavior presents as non-randomness in agent interaction statistics (Chan 2011).

Specifically, we look at the *lag* 1 correlation which is the ACF coefficient value between time steps $t$ and $t+1$ in the series. This metric is of particular interest as it does not require global system knowledge. It therefore may be a candidate metric for an individual agent to use to decide on-line if emergence is occurring and perhaps adjust its behavior accordingly.

## 4 EXPERIMENTAL ANALYSIS

In this experimental analysis, we aim to study the effect of lossless and lossy communications on the emergent behavior exhibited by the swarm. The simulation environment chosen for this study was the multi-agent simulator MASON (Luke et al. 2005). MASON is a Java-based, discrete event simulator with a focus on networks and execution speed. Time advances in steps which have been equated to one second. Time within each step then proceeds according to the transmission time of node transmissions (queuing, propagation and other delays are ignored). Nodes are moved at the end of each second after all transmissions have have taken place. Note that physical platform effects such as maneuverability are ignored and nodes can occupy the same physical space.

The effectiveness of swarm operation ultimately depends on information delay since the algorithm under test positions nodes based on the knowledge of their peers' position. More simply, how up-to-date is the information being used to make movement decisions? In the simulation, there are two groups of variables that affect this delay. The first being communications factors and the second being algorithmic factors. Communications in the simulation were modeled via:

1. *Path Loss* - Electromagnetic waves are attenuated as they travel through the environment. This radio propagation was modeled using the Friis free space transmission equation in conjunction with the Log-Distance Path Loss (LDPL) model. The receive power in decibels is then calculated as

$$P_{r\ LDPL} = P_t + G_t + G_r + 20\log_{10}\left(\frac{\lambda}{4\pi d_0}\right) - 10n\log_{10}\frac{d}{d_0},$$

   where $P_r$ is receive power in decibels referenced to one milliwatt (dBm), $P_t$ is transmit power (dBm) $G_t$ is transmitter gain in decibels (dB), $G_r$ is receiver gain(dB), $\lambda$ is wavelength (m), $d_0$ is the reference (far-field) distance (m), $n$ is the unit-less path loss exponent and $d$ is the distance between transceivers (m) (Rappaport 2002).
2. *Shadowing* - A Gaussian random variable may be added to the receive power equation above to account for shadowing caused by clutter along the propagation path. This model is known as Log-Normal Shadowing (LNS) and takes the form $P_{r\ LNS} = P_{r\ LDPL} + \chi_\sigma$ where $\chi_\sigma$ is a random variable such that $\chi \sim \mathcal{N}(0,\sigma^2)$ with a standard deviation of $\sigma$ dB (Rappaport 2002).
3. *SNR Packet Reception* - Fundamental to packet reception is the Signal-to-Noise Ratio (SNR) of the receiving node; nodes will only receive a transmitted packet if an appropriate SNR threshold is met. Nodes do not have a minimum receive sensitivity and the edge set at time $t$ is defined as $E_i(t) = \{(i,j) : i,j \in A, i \neq j, \mathrm{SNR}(i,j) \geq SNR_{\mathrm{threshold}}\}$ which implies $j \in N_i(t)$.
4. *Contention* - Wireless communications take place over a shared-medium, that is, all nodes are contending for the same medium in order to transmit. Media Access Control (MAC) protocols regulate a medium's availability to the node. A common type of MAC is the contention-based, Carrier-Sense Multiple Access (CSMA). This scheme adopts a 'listen before you talk' policy where (ideally) no two nodes can transmit simultaneously if they are within reception range of each other. A CSMA style transmission rule was modeled for nodes within the simulation. A single node is randomly selected for transmission, then any other node in its reception range is removed from the pool of possible transmitters. In this way, simultaneous transmissions are removed while making medium access fair for all nodes.

   Time within steps is advanced via the transmission time. Transmission time refers to the time required to put the data 'into the air'. For example, to transmit 100 bits at a data rate of 100 bits per second, would require one second. In this model, the transmitting node would use the channel (and consequently block other possible transmitters) for a full second.
5. *Jamming* - Two nodes that are outside of reception range of each other may simultaneously transmit to the same receiver. While some strategies exist to avoid this (and other common problems of this nature), they are not considered here. In the simulation, when considering the reception of a

signal, any other simultaneous transmission contributes to the noise at the receiver, that is, noise is calculated via the equation $n_r = n_f + \sum_{i=1}^{k} P_i$, where $n_r$ is the total noise at the receiver in milliwatts, $n_f$ is the noise floor of the device, and $P_i$ is the power at the receiver from transmitter $i$ where $k > 1$ if there are simultaneous transmitters.

The algorithmic factors that are explored in the study are:

1. *Protocol Update Rate* - A parameter is available to adjust how often a node adds positional updates to the send queue. Protocol packets are 98 bytes, assuming a UDP/IP and ethernet MAC header. This payload contains a single integer for node identification, and three double floats to encode the Cartesian coordinates of the node. Note that payload sizes are an approximation and ignore things such as error correction. Protocol packets are generated at regular intervals and added to the send queue.
2. *User Traffic* - Nodes are able to send non-protocol traffic which has a two-fold effect. Firstly, it delays protocol traffic within the send queue of each node (assuming no traffic prioritization). Secondly, it uses up valuable medium time, blocking other nodes from potentially sending protocol traffic.
   User traffic is generated using the IEEE 802.16-4IPP model (Baugh and Huang 2001). This model simulates generation of common self-similar internet HTTP/TCP and FTP traffic. It uses a superposition of four Interrupted Poisson Processes (IPP) operating on different time scales. Each IPP is modeled as a two-state Markov chain where a node can be either be in an *ON* state or an *OFF* state. When in the *ON* state, the node produces (bursty) traffic via a Poisson process at a constant rate of $\lambda$ packets per second. While the model was produced for the 802.16 standard (commonly known by its commercialized name 'WiMAX') nearly 20 years ago it is still in use today; most recently, to generate traffic in aerial nodes participating in DTN QoS experiments (Martinez-Vidal, Marti, Sreenan, and Borrell 2016). A single 4IPP generator is initiated for each node with the 4IPP parameters being scaled for an input user traffic rate. User packets use the 4IPP model packet size of 192 bytes.

Several other algorithmic parameters will also have a large bearing on the swarm's performance:

1. *Node Speed* - The algorithm under test is fundamentally based on movement, therefore the movement speed of the nodes will play an important role in the effectiveness of the swarm. Within the simulation, nodes move at the given speed or are stationary and do not use any physical platform modeling.
2. *Data Caching* - Caching of peer information is required for the algorithm to work; caching protocol information for too long leads to data obsolescence. However, cleaning the cache too often leaves the algorithm with little to no information to use. This parameter should be explored for optimal performance but given it is a purely algorithmic parameter it is set to a fixed value of two seconds for all experiments.
3. *Node Number* - As the number of swarm nodes increases, the medium contention also increases.

### 4.1 Results

In the following, unless otherwise stated, nodes transmit at 0dBm and have 0dB antenna gain. Radio parameters mimic a wifi-like waveform propagating in an outdoor environment with some clutter. As such, the radio frequency is 2.412GHz (IEEE 802.11 channel 1), has a path-loss exponent of 2.68, with a shadowing random variable of 3dB and a noise floor of -95dBm. Propagation values are taken from the 'Woodland' environment in (Gay-Fernández and Cuiñas 2013). The data rate was left fixed at the slowest wifi (broadcast) rate of $1\text{Mbs}^{-1}$ and a signal reception SNR threshold of 4.

Nodes are initially randomly distributed closely around point (500, 500) in a 1000 units square simulation environment and the attraction-repulsion algorithm has parameters $R_{\min} = 60$m and $R_{\max} = 70$m.

### 4.1.1 Lossless Communications

We first analyze a lossless communication scenario to provide baseline values for all metrics under ideal conditions. Table 1 shows the parameter values for the experiment with the algorithm running under a lossless communications model.

Table 1: Parameters for the attraction-repulsion ideal baseline experiment.

| Parameter | Value |
|---|---|
| SNR Threshold (dB) | $-\infty$ (no threshold) |
| MAC Scheme | None (no contention) |
| Number of nodes | 25 |
| Node speed | 1.0 |
| Update Rate (Hz) | $\infty$ (information always available) |
| User traffic (KB$s^{-1}$) | 0 |

Figure 1 shows the metrics after $T = 600$ steps for a particular run. Unsurprisingly, they indicate perfect performance of the algorithm. The network is consistently composed of one connected component with zero articulation points (Figure 1a). It also makes use of the allowed propagation range (see Figure 1b), expanding linearly until it nears a stable configuration (some variation is due to Monte-Carlo area estimation). Figures 1d and 1e show that there are initially 25 state changes per time step. This is a consequence of all nodes undergoing an effective interaction in order to space themselves apart. The amount of state changes dramatically decreases once all nodes near the desired spacing. More interestingly, the correlogram of the time-series state change, Figure 1f, shows a high degree of correlation between time-steps, even beyond the first lag. The bounds in Figure 1f represent a region within which no correlation is present. Note that the first data point in any correlogram (which represents a lag of zero) is always one since any value is maximally correlated with itself. Table 2 summarizes the lossless and lossy experiments over 10 differently-seeded runs.

### 4.1.2 Lossy Communications

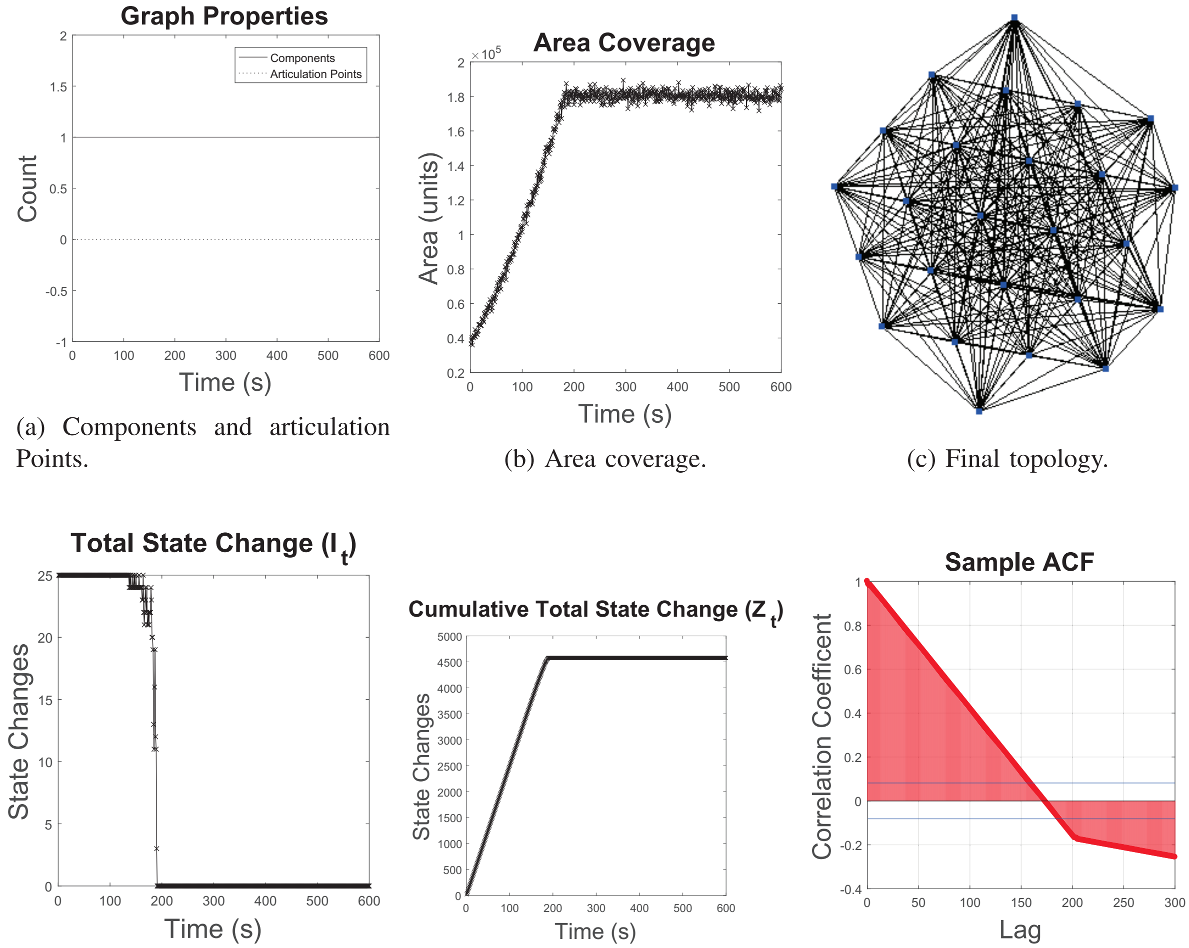
To better understand the performance of the algorithm in realistic communication scenarios, we next disrupt data dissemination within the algorithm through the addition of user traffic. We expect to see poorer performance of the metrics as compared to the lossless case. However, we also attempt to mitigate this decrease in performance by increasing the protocol update rate.

The experiment varies the protocol update rate over 1, 5 and 10Hz and the user traffic rate over 0, 10, 25 and 50 KBs$^{-1}$ per node using 25 nodes with a movement speed of 1ms$^{-1}$. The simulations run for 600 steps and results aggregated over 10 runs.

Figure 2a shows the results for the experiment which reveals several interesting features. The first thing to note is that as the user traffic rate increases, the first-lag ACF coefficient decreases since the user traffic is disrupting the regular protocol traffic. This is mitigated to some extent by increasing the rate at which protocol traffic is transmitted. Now let us examine this reduction in coefficient value with our

Table 2: Comparison of end-of-run metric values for the lossless and two lossy cases with user traffic in KBs$^{-1}$ and protocol updates in Hz.

| | **Experiment** | | | | | |
|---|---|---|---|---|---|---|
| | Lossless | | 10KBs$^{-1}$, 10Hz | | 50KBs$^{-1}$, 1Hz | |
| **Metric** | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ | $\mu$ | $\sigma$ |
| Area (units)$\times 10^5$ | 1.7974 | 0.0396 | 1.8239 | 0.0423 | 1.5243 | 0.0926 |
| First lag of ACF | 0.9709 | 0.0071 | 0.9666 | 0.0070 | 0.5459 | 0.0115 |




(a) Components and articulation Points.

(b) Area coverage.

(c) Final topology.

(d) $I_t$ time series.

(e) $Z_t$ time series.

(f) Correlogram of $x_i$ for 300 lags.

Figure 1: Lossless experiment results for a particular run.

purpose-driven metrics. In Figure 2b we notice that in many cases the area achieved is slightly better than the lossless case above. How can this be? It is postulated that a slight disruption in protocol traffic permits less well-connected topologies such as in Figure 2d. However given the error bounds on the area estimation, a more precise area measure is required to confirm this result. As the disruption becomes too great, protocol traffic begins to hit the two second cache cleaning limit and nodes have no neighbors to use to position themselves. They therefore remain stationary and produce a more ‘cluttered’ topology like that in Figure 2e. Again, this is mitigated by an increased protocol traffic rate. These topologies show a less structured version of the lossless case, Figure 1c.

Figure 2c shows the mean number of articulation points formed throughout the experiments. In general, few articulation points are created during the experiments and as user traffic increases and the topologies become more cluttered, fewer points are created since nodes are closer together. It is likely that the few articulation points that are formed are due to the random variable associated with the log-normal shadowing propagation model and only exist for a short time.

Another noteworthy feature is the very low lag 1 autocorrelation coefficient for the 1Hz update rate and 10KBs$^{-1}$ user traffic rate in Figure 2a, yet it performs equivalently with 5Hz and 10Hz update cases in the area metric. This is explained by efficiency. While all cases reach near optimal area coverage, the

1Hz update case does so much slower, as is shown in Figure 2f. The 1Hz update case permits ‘enough’ emergence for the algorithm to work, but not enough to work very efficiently.

For comparison, Figures 2g, 2h and 2i show the most challenged case of an update of 1Hz and user traffic of $50\text{KBs}^{-1}$ for a particular run. The correlogram shows much less correlation than the lossless case in Figure 1f. The total state change graph initially has 25 state changes as all nodes begin spreading out. However it also contains times where zero state changes occur since the user traffic blocked the protocol traffic completely. It mildly improves once nodes have spread out (and medium contention has lessened) but the number of state changes still contains a large amount of noise. At this point, the system has converged, albeit to a noisy state. This is easier to discern from the total cumulative state change graph Figure 2i. Here, we can see two distinct gradients with the knee occurring near time step 150 indicating the convergence point. This can easily be seen for the lossess case, Figure 1e, as well.

### 4.2 Discussion

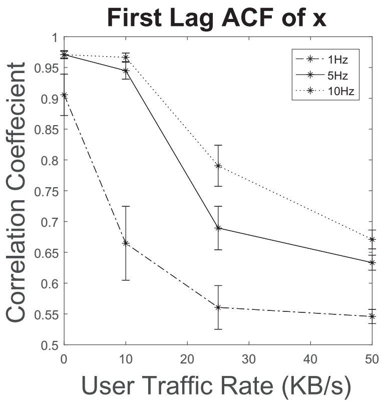
From examining the correlogram for the lossless communications case in Figure 1f, we can see the first lag coefficient is close to 1, meaning a near maximum correlation between the current state and the next. We interpret this to mean that a high level of emergence is present in this case. This is visually validated by examining the evolution of the network (Figure 1c shows the final topology). In the lossy scenario shown in Figure 2g, communications are disrupted (by increasing user traffic from 0 to 50 $\text{KBs}^{-1}$) in such a way that the state change time-series appears to be random, or at least contains a large noise signal within it. Consequently, the first lag coefficient has dropped to approximately 0.6. This trend of decreasing autocorrelation value with increasing user traffic can be seen in Figure 2a and is interpreted to be the *breakdown* of emergence. This breakdown of emergence then has significant and negative effects on the outcome of the algorithm as measured by the purpose-driven metrics. Thus, for this algorithm, the autocorrelation function provides a *continuous* indicator of inherent emergence. Furthermore, its use on the state change time-series of individual agents means that the metric is also *local* and therefore does not require global agent knowledge to be useful.

This analysis is conducted under the assumptions expressed in Section 3.3. Moreover, the ACF approach requires validation for different swarming algorithms, and ultimately under real communications and mobility conditions. Under these assumptions however, the full arsenal of time-series signal-processing tools are at our disposal and could be used to extend and further explore this interaction time-series approach.

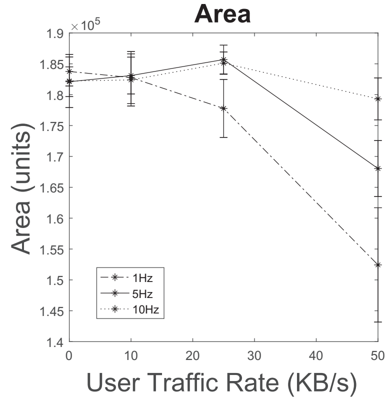
## 5 CONCLUSION

Communication is assumed to be perfect by most swarming mechanisms, however this is not the case in real-world environments. In this paper, we show the effect of degraded communications on the production of emergent behavior in the attraction-repulsion swarm algorithm. In our analysis, we employ metrics that measure the effectiveness of the swarm for a specific purpose, as well as a metric that indicates if emergence is present. We selected the agent interaction statistics pertaining to state changes as a metric and introduced the use of the autocorrelation function. Our analysis shows that under perfect communication conditions, the attraction-repulsion algorithm built a well-connected mesh network where state changes in individual nodes were highly correlated with each other. When challenged with user traffic, emergence broke down and reduction in the autocorrelation lag coefficient values, and therefore an increase in randomness, in the time-series of state changes of individual agents was shown. This affected the purpose-driven metrics in unexpected ways.

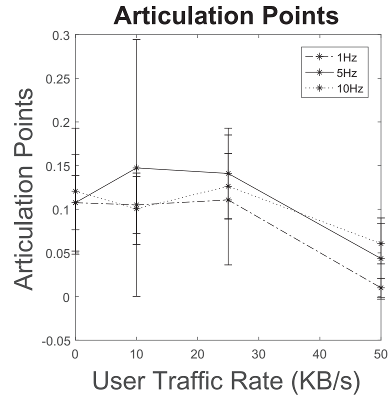
This study has also demonstrated the need to consider the impact of communication load and protocol contention on the production of a desired emergent property. In this case, efficiency and resultant network topologies differed substantially to the ideal, lossless communications scenario. Practically, this highlights the need for protocol related traffic prioritization through quality-of-service based approaches to ensure the realization of the desired emergent behavior.



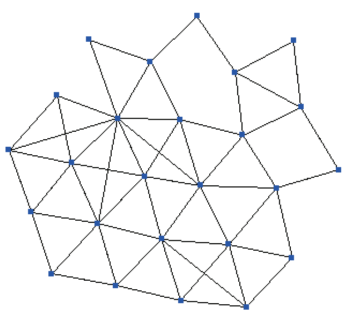

(a) First lag of the ACF of $x_i$ vs user traffic for different update rates.



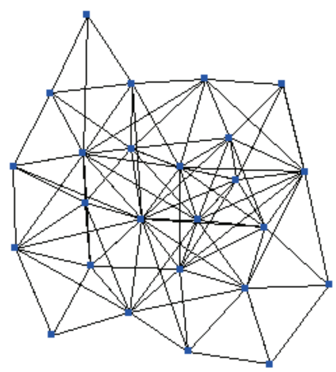

(b) Area coverage vs user traffic for different update rates.



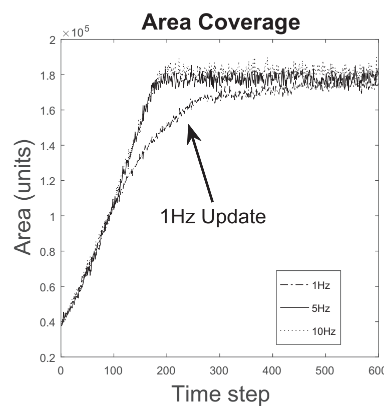

(c) Articulation points vs user traffic for different update rates.



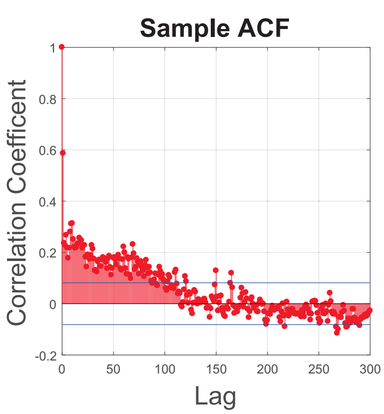
(d) Final topology for a 5Hz update and user traffic of $25\text{KBs}^{-1}$.



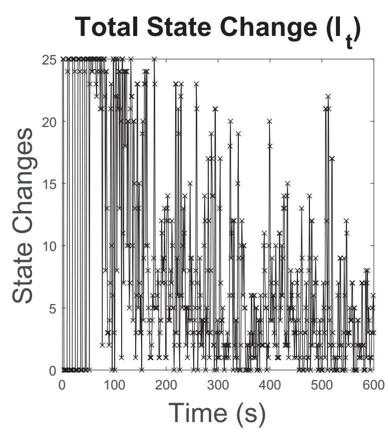
(e) Final topology for a 1Hz update and user traffic of $50\text{KBs}^{-1}$.



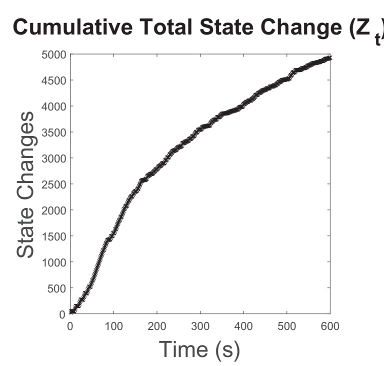

(f) Area coverage evolution for user traffic of $10\text{KBs}^{-1}$ with different update rates.




(g) Correlogram of $x_i$ for an update rate of 1Hz and user traffic of $50\text{KBs}^{-1}$.




(h) Total state change for a 1Hz update and user traffic of $50\text{KBs}^{-1}$.




(i) Cumulative total state change for a 1Hz Update and user traffic of $50\text{KBs}^{-1}$.

Figure 2: Lossy experiment results. Error bars indicate one standard deviation.

From an analysis perspective, the study also shows that the use of the autocorrelation function in examining the state change time-series of individual agents for emergence can be beneficial. This is an important result since global knowledge of agent statistics is not required.

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