# DRAFT: Trust Framework Operation in Autonomous Marine Communications Environments

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**Abstract.** This paper presents a Trust Management Framework (TMF) for Marine Autonomous Networks, We present a comparative study on the operation and performance of such trust frameworks between a typical terrestrial and the harsh underwater communications environment, examining the scaling factors involved (periodicity, physical spacing, etc.) in comparing and contrasting these environments.
We demonstrate the need for a different approach towards metric selection and trust-timing in such constrained networks.

**Keywords:** ad-hoc, MANET, trust, marine, underwater, acoustic

## 1 Introduction

As mobile ad-hoc networks (MANETs) grow beyond the terrestrial arena, their operation and the protocols designed around them must be reviewed to assess their suitability and optimality in different communications environments to ensure their continued security, reliability, and performance.

Trust Management Frameworks (TMFs) provide information to assist the estimation of future states and operations of nodes within networks. This information is used to optimize the performance of a network against malicious, selfish, or defective misbehaviour by one or more nodes. Previous research has established the advantages of implementing TMFs in 802.11 based mobile ad-hoc networks (MANETs), particularly in terms of preventing selfish operation in constrained collaborative systems [7], and maintaining throughput in the presence of malicious actors [1]

Current TMFs generally use a single type of observed action to derive trust values, i.e. successfully forwarded packets. These observations then inform future decisions of individual nodes, for example, router selection [8].

Recent work has demonstrated use of a number of metrics to form a 'vector of trust. Multi-parameter trust framework for MANETs (MTFM)[4], uses a range of physical metrics beyond PLR to form a vector of trust. This vectorized trust allows a system to detect and identify the tactics being used to undermine or subvert trust. To date this work has been limited to terrestrial, RF based networks. As autonomous underwater vehicles (AUVs) become more capable, and economical, they are being used in many applications. These applications are tending towards using the collective behaviour of teams or fleets of these AUVs to accomplish tasks [2]. With this use being increasingly isolated from stable communications networks, the establishment of trust between nodes is essential for the reliability and stability of such teams. As such, the application of Trust methods developed in the terrestrial MANET space must be re-appraised for application within the challenging underwater communications channel.

The paper is laid out as follows. In Section 2 we discuss Trust and Trust Management Frameworks, defining our terminology and reviewing the justifications for the use and development of Trust Management Frameworks. In Section 3, we review selected features of the underwater communications channel, highlighting particular challenges and differentials against terrestrial equivalents. In Section 2.1 we establish the requirement for trust in acoustic marine networks, extending and expanding on the generic assessment given in 2.1. In Section 4, we establish an experimental configuration for the marine space, and review the scenarios and results presented in [5]. In Section 5, we present our findings in trust establishment and malicious behaviour detection, comparing with OTMF and Beta.

The contributions to the field of this paper are: A Trust Management Framework applicable to Underwater MANETs, a study on the comparative operation and performance between terrestrial and underwater MANETs using TMFs, and a review of metric suitability for Trust Management Frameworks in marine environments, informing future metric selection for experimenters and theorists.

## 2    Trust and Trust Management Frameworks

### 2.1    Trust in MANETs

Trust is the level of confidence one agent has in another to perform an action. The distributed and dynamic nature of MANETs mean that it is difficult to maintain a trusted third party (TTP) or evidence based trust system such as Certificate Authorities or using Public Key Infrastructures (PKI). Distributed trust management frameworks aim to detect, identify, and mitigate the impacts of malicious actors by distributing per-node assessments and opinions to collectively self-police behaviour.

Various models and algorithms for describing trust and developing trust management in distributed systems, P2P communities or wireless networks have been considered. Taking some examples;

- *The Objective Trust Management Framework* takes a Bayesian Beta function to model per-link Packet Loss Rate (PLR) over time, combining "Trust" and

"Confidence of Assessment" into a single value [8]. OTMF however does not appropriately combat multi-node-collusion in the network [3].

– *Trust-based Secure Routing*[11] demonstrated an extension to Dynamic Source Routing (DSR), incorporating a Hidden Markov Model of next-hop network, reducing the efficacy of Byzantine attacks.
– *CONFIDANT*[1] presented an approach using a probabilistic estimation of PLR, similar to OTMF, also introducing a topology weighting scheme that weighted trust assessments based on historical experience of the reporter.
– *Fuzzy Trust-Based Filtering*; [9] presents the use of Fuzzy Inference to adapt to malicious recommenders using conditional similarity to classify performance with overlapping Fuzzy Set Membership, filtering assessments across a network.

OTMF, CONFIDANT, and Fuzzy Trust-Based Filtering can be generalised as single-value probabilistic estimation, based around a Bayesian idea of taking a binary input state and collaboratively generating an idealised Beta Distribution of the future states of that input. This expectation value is $\text{beta}(p|\alpha,\beta) \rightarrow E(p) = \frac{\alpha}{\alpha+\beta}$ where $\alpha$ and $\beta$ represent the number of successful and unsuccessful interactions respectively.

These single metric TMFs provide malicious actors with a significant advantage if their activity is undetectable by that metric. In the case where the attacker can subvert the TMF, the metric under assessment by that TMF does not cover the threat mounted by the attacker. In turn, this causes a super-linearly negative effect in the efficiency of the network as the TMF is assumed to have reduced the possible set of attacks when it has made it more advantageous to attack a different part of the networks operation. An example of such a behaviour would be the case in a TMF focused on PLR where an attacker selectively delays packets going through it, reducing overall throughput but not dropping any packets. Such behaviour would not be detected by the TMF.

Also, there are situations where the observed metrics will include significant noise and those observations occurring at irregular, sparse, intervals. Conventional approaches such as Bayesian prior probability estimation do not produce trust values that reflect the underlying reality and context of the metrics available, as they require a-prioi assumption that the trust value under exploration has an expected distribution, that distribution is mono-modal, and the input metrics are binary. In scenarios with variable, sparse, noisy metrics, estimating the distribution is difficult to accomplish off-line in advance. The binary requirement of Bayesian modelling requires metric threshold discrimination, which if applied to non-binary inputs, discards useful information and generates a phase transition area where a proportion of "unfair" behaviour does not impact the assessed trust values, but impacts system performance [13].

While all of the discussed TMFs take topology into account, they do not take account of environmental factors that may be inducing poor performance.

## 2.2   Grey Theory Operation

Grey Theory performs cohort based normalisation of metrics at runtime. This creates a more stable contextual assessment of trust, providing an "grade" of trust compared to other observed nodes in that interval, while maintaining the ability to reduce trust values down to a stable assessment range for decision support without characterising every environment entered into. This presents a stark difference between the Grey and Probabilistic approaches. Grey assessments are relative in both fairly and unfairly operating networks. Nodes will receive mid-range trust assessments if there are no malicious actors as there is no-one else "bad" to compare against, and variations in assessment will be primarily driven by topological and environmental factors. Future work will investigate the stability of GRA under multi-node collusion.

Guo[4] demonstrated the ability of Grey Relational Analysis (GRA)[17] to normalize and operationally combine disparate traits of a communications link such as instantaneous throughput, received signal strength, etc. into a Grey Relational Coefficient, or a "trust vector".

In the case of the terrestrial communications network used in [4], the observed metric set $X = \{x_1, \ldots, x_M\}$ representing the measurements taken by each node of its neighbours at least interval, is defined as $X = $ [packet loss rate, signal strength, data rate, delay, throughput]. The trust vector is given as

$$\theta_{k,j}^t = \frac{\min_k |a_{k,j}^t - g_j^t| + \rho \max_k |a_{k,j}^t - g_j^t|}{|a_{k,j}^t - g_j^t| + \rho \max_k |a_{k,j}^t - g_j^t|}$$

$$\phi_{k,j}^t = \frac{\min_k |a_{k,j}^t - b_j^t| + \rho \max_k |a_{k,j}^t - b_j^t|}{|a_{k,j}^t - b_j^t| + \rho \max_k |a_{k,j}^t - b_j^t|} \tag{1}$$

where $a_{k,j}^t$ is the value of a observed metric $x_j$ for a given node $k$ at time $t$, $\rho$ is a distinguishing coefficient set to 0.5, $g$ and $b$ are respectively the 'good' and 'bad' reference metric sequences from $\{a_{k,j}^t k = 1, 2 \ldots K\}$, e.g. $g_j = \max_k(a_{k,j}^t)$, $b_j = \min_k(a_{k,j}^t)$ (where each metric is selected to be monotonically increasingly positive for trust assessment, e.g. throughput).

Weighting can be applied before generating a scalar value which allows the identification and classification of untrustworthy behaviours.

$\theta$ and $\phi$ are then scaled to $[0, 1]$ using the mapping $y = 1.5x - 0.5$.

$$[\theta_k^t, \phi_k^t] = \left[ \sum_{j=0}^{M} h_j \theta_{k,j}^t, \sum_{j=0}^{M} h_j \phi_{k,j}^t \right] \tag{2}$$

Where $H = [h_0 \ldots h_M]$ is a metric weighting vector such that $\sum h_j = 1$, and in the basic case, $H = [\frac{1}{M}, \frac{1}{M} \ldots \frac{1}{M}]$ to treat all metrics evenly. The $[\theta, \phi]$ values are reduced into a scalar trust value by

$$T_k^t = \frac{1}{1 + \frac{(\phi_k^t)^2}{(\theta_k^t)^2}} \tag{3}$$

Add to future work section

This trust value minimises the uncertainties of belonging to either best $(g)$ or worst $(b)$ sequences in (1).

GRA, combined with a fuzzy whiteisation model (4), and a topology-aware weighting scheme(5) provide capability to both detect the existence of a malicious agent within the network, and to classify what trust metrics that attacker is manipulating.

There are three classes of topological trust relationship; Direct, Recommendation, and Indirect. To take the example of a node $n_i$ monitoring the trust of another, target, node, $n_j$; the Direct relationship is $n_i$'s own observations $n_j$'s behaviour. In the Recommendation case, a node $n_k$, which shares Direct relationships with both $n_i$ and $n_j$, gives its assessment of $n_j$ to $n_i$. The Indirect case, similar to the Recommendation case, the recommender $n_k$, does not have a direct link with the observer $n_i$ but $n_k$ has a Direct link with the target node, $n_j$.

These relationships give us node sets, $N_R$ and $N_I$ containing the nodes that have recommendation or indirect, relationships to the observing node respectively.

$$f_1(x) = -x + 1$$
$$f_2(x) = \begin{cases} 2x & \text{if } x \leq 0.5 \\ -2x + 2 & \text{if } x > 0.5 \end{cases} \tag{4}$$
$$f_3(x) = x$$

$$T_{i,j}^{net} = \frac{1}{2} \cdot \max_{s}\{f_s(T_{i,j})\}T_{i,j} + \frac{1}{2}\frac{2|N_R|}{2|N_R| + |N_I|} \sum_{n \in N_R} \max_{s}\{f_s(T_{i,n})\}T_{i,n} \tag{5}$$
$$+ \frac{1}{2}\frac{|N_I|}{2|N_R| + |N_I|} \sum_{n \in N_I} \max_{s}\{f_s(T_{i,n})\}T_{i,n}$$

## 3   Marine Acoustic Networks

The key challenges of underwater acoustic communications are centred around the impact of slow and differential propagation of energy (RF, Optical, Acoustic) through water, and it's interfaces with the seabed / air. The resultant challenges include; long delays due to propagation, significant inter-symbol interference and Doppler spreading, fast and slow fading due to environmental effects (aquatic flora/fauna; surface weather), carrier-frequency dependent signal attenuation, multipath caused by the medium interfaces at the surface and seabed, variations in propagation speed due to depth dependant effects (salinity, temperature, and pressure), and subsequent refractive spreading and lensing due to that same propagation variation[14].

The attenuation that occurs in an underwater acoustic channel over a distance $d$ for a signal about frequency $f$ in linear power as $A_{\mathrm{aco}}(d, f) = A_0 d^k a(f)^d$ and in $dB$ form as

$$10 \log A_{\mathrm{aco}}(d, f)/A_0 = k \cdot 10 \log d + d \cdot 10 \log a(f) \tag{6}$$

where $A_0$ is a unit-normalising constant, $k$ is a spreading factor (commonly taken as 1.5), and $a(f)$ is the absorption coefficient, expressed empirically using Thorp's formula (7) from [16]

$$10 \log a(f) = 0.11 \cdot \frac{f^2}{1 + f^2} + 44 \cdot \frac{f^2}{4100 + f^2} + 2.75 \times 10^{-4} f^2 + 0.003 \tag{7}$$

Refractive lensing and the multipath nature of the medium result in apparently "line of sight" propagation being extremely unreliable for estimating distances to targets, as the first arriving beam has as the very least bent in the medium, and commonly has bounced between the surface/seabed before arriving at a receiver, creating secondary paths that are sometimes many times longer than the first arrival path, generating symbol spreading over orders of seconds depending on the ranges and depths involved. Further, this affect is usually anisotropic with different depths between transmitter and receiver, meaning that any variation in depth across a channel, greatly impacts the characteristics of that channel.

Comparing $A_{aco}(d, f)$ with the RF Free-Space Path Loss model $A_{\mathrm{RF}}(d, f) \approx \left(\frac{4\pi df}{c}\right)^2$, the impact of range on signal power is exponential underwater, rather than quadratic in RF space ($A_{\mathrm{aco}} \propto f^{2d}$ vs $A_{\mathrm{RF}} \propto (df)^2$).

While both frequency dependant factors are quadratic, approximating the factors in (7), $f \propto A_{\mathrm{aco}}$ is at least 4 orders of magnitude higher than $f \propto A_{\mathrm{RF}}$

### 3.1   Trust in Marine Networks

With increasing demand for smaller, more decentralised marine survey and monitoring systems, and a drive towards lower per-unit cost, TMFs are going to be increasingly applied to the marine space, as the benefits they would present are significant. Beyond the constraints of the communications environment (Section 3), the move towards smaller decentralised systems has knock on pressures in terms of battery capacity, on-board processing, locomotion, and prioritisation of sensor payloads. These pressures simultaneously present opportunities and incentives for malicious or selfish actors to appear to cooperate fairly while not reciprocating that fairness in order for instance to conserve power. These multiple aspects of potential incentives, trust, and fairness do not directly fall under the scope of single metric trusts such as OTMF, CONFIDANT, etc., and this context indicates that a multi-metric approach would provide more actionable results.

# 4 Initial System Model Characterisation

## 4.1 Mobility, Topology, and Communications

Four Mobility scenarios were used in [5] to explore trust behaviour; all nodes static, a central node $n_1$ performing a random walk with other nodes remaining static, all nodes but the central node ($n_1$) randomly walking, and all nodes randomly walking.

The six nodes are placed as per Fig. 1, and each node is on average 100m from each other. The use of six nodes and the particular layout enables the investigation of the three trust relationships based on minimum path topologies, such that the node generating the trust assessments, $n_0$ has Direct, Recommendation, and Indirect trust assessments available to it from itself, $[n_2, n_3]$, and $[n_4, n_5]$ respectively.

In all of the scenarios, each link from $n_i \rightarrow n_j$ periodically sent 10 second bursts of Constant Bit Rate (CBR) style traffic.
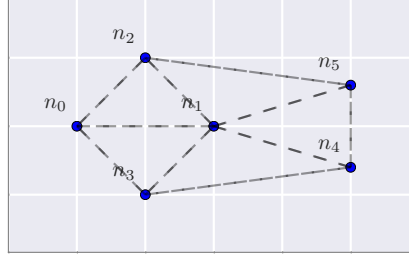


Fig. 1: Initial layout with nodes spaced an average of 100m apart

Guo demonstrated that when compared against OTMF and Beta trust assessment, MTFM provided increased variation in trust assessment over time, providing more information about the nodes behaviour than packet delivery probability. By weighting the metrics used in MTFM, it was shown that the trust assessments could be used to identify the style of misbehaviour being performed within the network and by who.

We present a corollary method to investigate and apply this work to the Marine MANET field.

## 4.2 Simulation Background

Simulations were conducted using a Python based simulation framework, SimPy[12], with a network stack built upon the AUVNetSim stack[10], with transmission parameters (Table 1) taken from and validated against [16] and [15].

Given the differences in delay and propagation between RF and marine networks, it is natural that the same application rates (e.g. packet emission rates

or throughput) and node separations should not be assumed to be equivalent. Therefore, we characterise an operational zone of performance within which the network can operate normally.

Table 1: Comparison of system model constraints as applied between Terrestrial and Marine communications

| Parameter | Unit | Terrestrial | Marine |
|---|---|---|---|
| Simulated Duration | $s$ | 300 | 36000 |
| Simulated Area | $km^2$ | 0.7 | Various |
| Transmission Range | $km$ | 0.25 | 1.5 |
| Number of Nodes | | 6 | 6 |
| Physical Layer | | RF(802.11) | Acoustic |
| Propagation Speed | $m/s$ | $3 \times 10^8$ | 1490 |
| Center Frequency | $Hz$ | $2.6 \times 10^9$ | $2 \times 10^4$ |
| Bandwidth | $Hz$ | $22 \times 10^6$ | $1 \times 10^4$ |
| MAC Type | | CSMA/DCF | CSMA/CA |
| Routing Protocol | | DSDV | FBR |
| Mobility | | Various | Various |
| Max Speed | $ms^{-1}$ | 5 | 2.4 |
| Data Rate | $bps$ | $10^6$ | 240 |
| Burst Counts | | 10 | 1 |
| Packet Size | bits | 4096 | 9600 |
| Destination Selection | | Random | Random |
| Single Transmission Duration | $s$ | 10 | 32 |
| Single Transmission Size | bits | $10^7$ | 9600 |

### 4.3   Scaling Considerations between Terrestrial and Underwater Environments

In this section we characterise the simulated communications environment, establishing an optimal packet emission rate for comparison against [5].

We establish a appropriate safe operating zone for marine communications by looking at the communications rate and physical distribution factors together across the four presented scenarios. In scaling the physical distribution of the nodes, we also scale the environment in which the nodes are restricted to, which has a significant impact on the number of potential runtime topologies, with nodes getting increasingly isolated as the environment space increases, leading to increasing packet losses and delays as routes are constantly broken, re-advertised and re-established. From Table 1, the operating transmission range of this model of acoustic communications is $\approx 6$ times further than 802.11, indicating that a suitable operating environment will have an area $\approx \sqrt{6}$ times the area of the 802.11 case. However, it was recognised in Section 3 that the relationship between

attenuation and distance is exponential underwater, so this would represent an upper bound of performance, where nodes begin approximately $400m$ apart.

We select throughput and end to end delay as the targeted aspects of the networks performance to optimise against. We take the ratio of throughput per second of delay as a combined proxy for this optimisation. $T/d$, shown in Fig. 3.

As the separation is increased, the emission rate at which the network becomes saturated decreases, reducing overall throughput. This throughput degradation is tightly coupled with the mobility scenario. For instance, in Fig. 2a, where all nodes are static, we do not see significant drops in saturation rates until we approach 800m, nearly double our estimate. However, in Figs. 2c and 2d, where the majority or all the nodes are randomly walking, and the saturation point collapses from 0.025pps at 300m to 0.015pps at 400m. These results indicate that the best area to continue operating in for a variety of node separations is at 0.015pps, and that a reasonable position scaling is from 100m to 300m, beyond which communication becomes increasingly unstable, especially in terms of end to end delay.

Add in Table here for delay characteristics too and talk about that, drawing the conclusion that 300 is better than 400 because you can increase the emission rate!
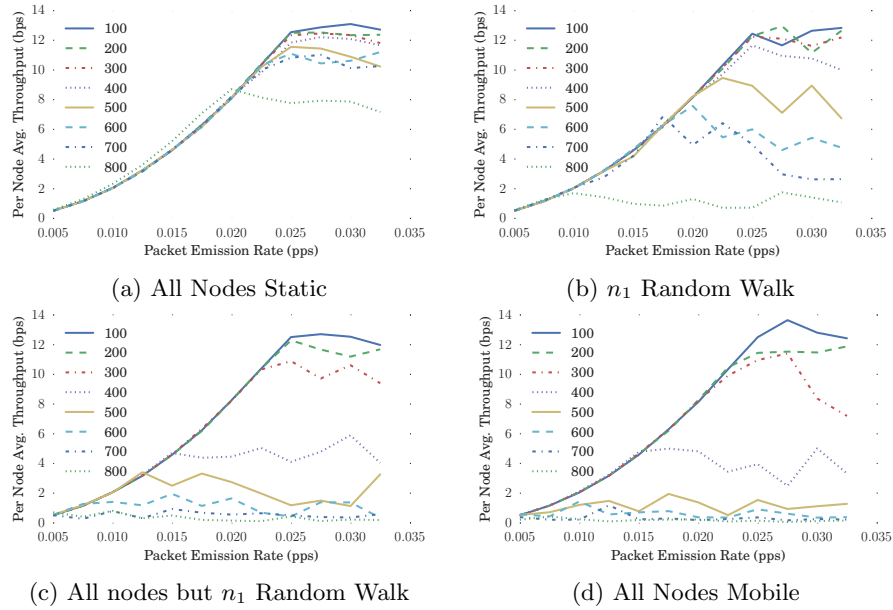


(a) All Nodes Static
(b) $n_1$ Random Walk
(c) All nodes but $n_1$ Random Walk
(d) All Nodes Mobile

Fig. 2: Throughput Characteristics for varying node separations across increasing packet emission rates

(a) All Nodes Static

(b) $n_1$ Random Walk

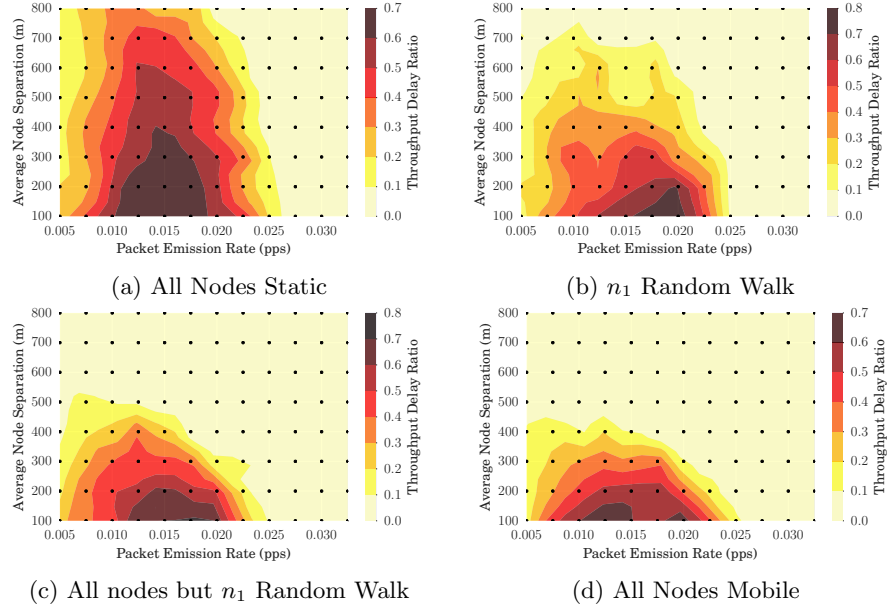(c) All nodes but $n_1$ Random Walk

(d) All Nodes Mobile

Fig. 3: Throughput/Delay Characteristics for varying node separations across increasing packet emission rates

## 5 Trust

Having established a safe operating range for comparison, at 300m separation with an emission rate of 0.015pps, we proceed to repeat the scenarios presented in [5]. We select an assessment period of 10 mins within a 5 hour 'mission' to scale in comparison to the relative bitrates experienced (1Mbps vs $approx$15bps).

The metrics available in the acoustic network do not universally match their counterparts in the 802.11 network in [5] Initially, all the available metrics (transmitted and received throughput and power, delay, and packet loss rate as calculated by aborted, unacknowledged, transmissions) were utilised for Grey assessment. Compared to [5], this metric set lacks a data rate quantity as the network is not dynamically adjusting bandwidth. In context of Grey Relational Coefficient generation (1), the best sequence $g$ was selected using the lowest PLR, delay, and powers, and the highest throughputs, with the worst sequence, $b$ the inverse of these.

The particular factors under discussion are the relative performance of MTFM against OTMF and Beta with respect to statistical stability across mobilities and in responsiveness to changing network behaviour. We establish a similar result set by initially tracking the resultant trust values established by MTFM in each of the four mobility scenarios, shown in Fig.4. For simplicity, we are primarily concerned with the observational trust relationship between node 0 and node 1, i.e. $n_0$'s assessment of the trustworthiness of $n_1$, or $T_{1,0}$. We are also concerned

with the opinions of $n_1$ provided to $n_0$ by other nodes, where $[T_{1,2}, T_{1,3}]$ and $[T_{1,4}, T_{1,5}]$ denote the sets of recommendation and indirect trust assessment respectively. We also include a set aggregate assessments; $T_{1,\mathrm{avg}}$, the flat average of direct trust assessments of $n_1$, $T_{1,\mathrm{Net}}$, an aggregate that weights assessments according to the network topology from (5), and $T_{1,\mathrm{MTFM}}$, the final MTFM trust assessment value based on both network topology and whitenisation from (4).

The variability in assessment is loosely tied to the mobility; in the static case (Fig. 4a), we see that the nodes close to $n_1$ ($[n_0, n_2, n_3]$) have reasonably consistent distributions, and as the range increases out to $[n_4, n_5]$, this variability increases. In the full mobility case, shown in Fig. 4b, this subjective variability is greatly increased, as the topology is highly dynamic and, as we'll discuss, delays on re-establishing routes are extremely volatile, perturbing the trust value. The aggregate trust values utilising the topology information ($T_{1,\mathrm{Net}}, T_{1,\mathrm{MTFM}}$) display a greatly decreased variation than those of the individual subjective observations in both cases.



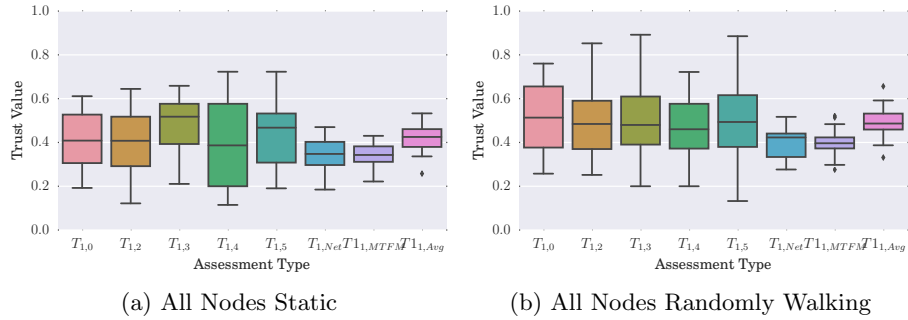(a) All Nodes Static          (b) All Nodes Randomly Walking

Fig. 4: MTFM Trust assessments for varying mobility options in the fair case

### 5.1 Weight Generation

For an arbitrary metric weight vector $H$, where the metric $m_j$ is emphasised as being twice as important as the other metrics, we form an initial weighting vector $H' = [1, 1, 1, 1, 2, 1]$ for $j = 4$ for example. We then scale that vector $H'$ such that $\sum H = 1$ by $H = \frac{H'}{\sum H'}$.

Using this process we can extract and highlight the primary aspects of an attack by comparing against the deviation from the 'fairness' set by other nodes in the network;

### 5.2 Comparison to OTMF and Beta

The same experiments were also performed utilising OTMF and Beta assessment as well as MTFM, providing like-for-like comparison of assessment at runtime.
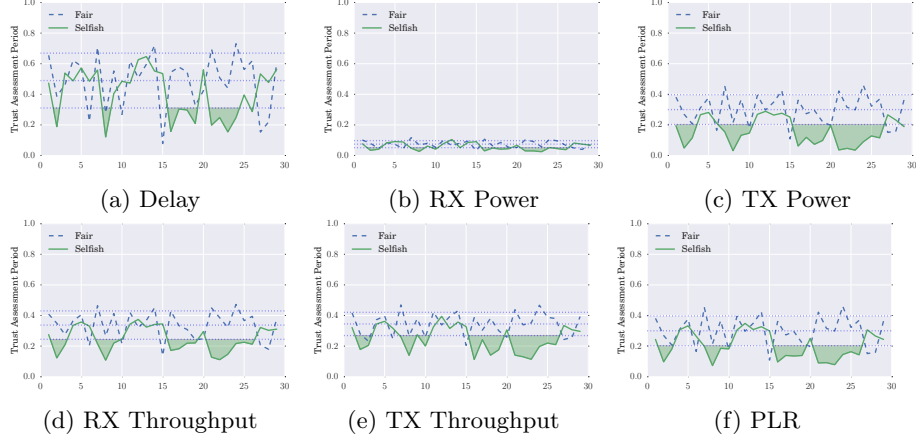
(a) Delay

(b) RX Power

(c) TX Power

(d) RX Throughput

(e) TX Throughput

(f) PLR

Fig. 5: $T_{1,0}$ in the All Static case for the Bad Mouthing Power Control behaviour, emphasising a different metric in turn, also showing the mean and $\pm\sigma$ of the fair assessment
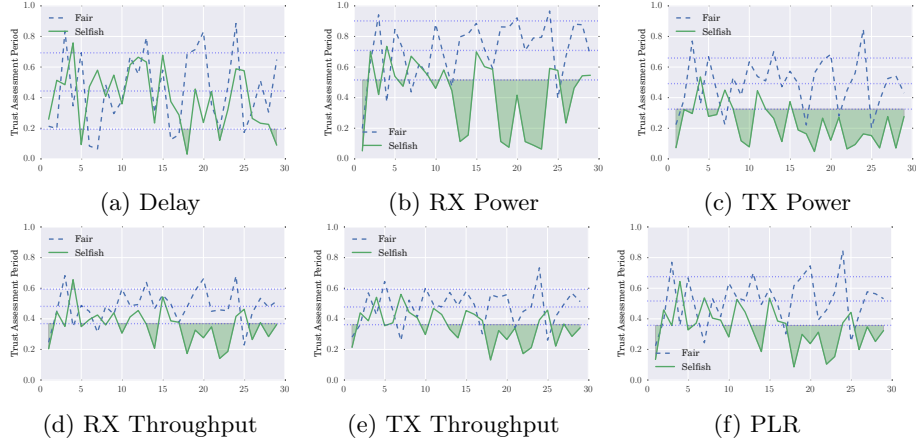


(a) Delay

(b) RX Power

(c) TX Power

(d) RX Throughput

(e) TX Throughput

(f) PLR

Fig. 6: $T_{1,0}$ in the Single Mobile case for the Bad Mouthing Power Control behaviour

(a) Delay        (b) RX Power        (c) TX Power

(d) RX Throughput        (e) TX Throughput        (f) PLR
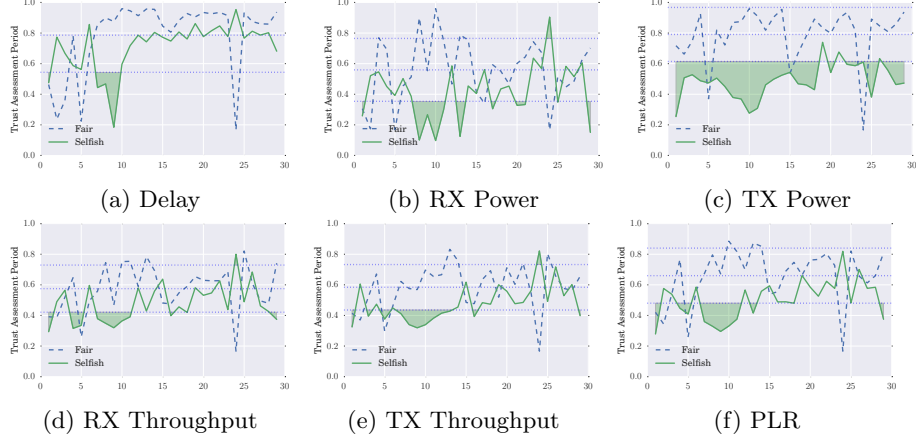
Fig. 7: $T_{1,0}$ in the All-but-$n_1$ Mobile case for the Bad Mouthing Power Control behaviour



(a) Delay        (b) RX Power        (c) TX Power
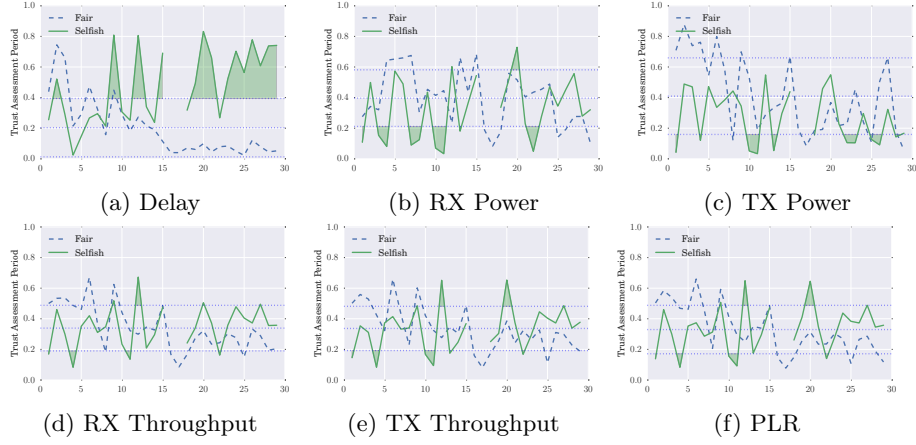
(d) RX Throughput        (e) TX Throughput        (f) PLR

Fig. 8: $T_{1,0}$ in the All Mobile case for the Bad Mouthing Power Control behaviour

It is important to note a distinction between the expectations of MTFM compared to other trust assessment frameworks; MTFM is primarily concerned with the identification of malicious or mistaken behaviours, and is relativistic in it's operation. That is to say that under Grey Theory, agents are compared against the worst current performances across metrics of other nodes and graded against them. OTMF and Beta in comparison are absolutist in their approach, and do not factor in a comparative metric for assessment; in the Bayesian book, you are good or bad regardless of what everyone else is doing. This relativistic versus absolutist differential is particularly stark when comparing mobility models.

MTFM keeps a steady assessment that the node under assessment, $n_1$, is behaving "OK" regardless of mobility model. However, the network itself is most under strain with full mobility, with the routing topology changing every few minutes, requiring route advertisements and request overheads that contend the already valuable channel.

Another difference is that computationally, MTFM is significantly more intensive than the relatively simple Beta / OTMF implementation, and the repeated metric matrix re-weighting required for reasonable behaviour detection is an area that requires work for it's optimisation.

As such, a hybrid system could be implemented, that used OTMF as a 'trigger' to detect potentially selfish or malicious behaviour, and allow MTMF to be triggered at less regular intervals.

### 5.3   Comparison under malicious behaviour

Introducing a malicious actor into a trusted network with the aim to identifying the actor and the form of the malicious action is the driving force behind this work. Guo introduces a range of malicious actors, including modification of the packet loss rate of routing nodes and limiting throughput on a per-link basis as well as a selection of combined misbehaviours.

In all cases, the malicious node is $n_1$, the node that $n_1$ is "attacking" is $n0$, who is also the primary observer, e.g. the value of trust under assessment is $T_{0,1}$

- *Single Metric Misbehaviours*
  - *Packet Loss Rate*: $n_1$ selectively denies $n_0$'s packets to reduce $n_0$'s apparent PLR from the perspective of the rest of the network.
  - *Signal Strength*: $n_1$ increases it's standard operating signal strength for all nodes *except* communications with $n_0$.
  - *Delay*: $n_1$ introduces artificial delays to it's communications with $n_0$
  - *Throughput*: $n_1$ artificially prioritises or de-prioritises it's communications with $n_0$ above/below everyone else so $n_0$ appears to be behaving unfairly.

Given that the established links are already heavily constrained, heavy handed attacks such as introducing selective PLR and adding to the already extreme and hugely variable delays would severely impact the general performance of the network beyond the scope of simple selfishness, effectively triggering saturation collapses in regions that the network should be stable.

In the interests of investigating the operation of trust and not of the network, we select a Signal Strength attack for $n_1$ to perpetrate on $n_0$, where $n_1$ increases it's own transmission power to everyone else.

The use of Forward Beam Routing and a RTS/CTS MACA MAC scheme from AUVNetSim in our particular simulation mitigate a significant number of potential packet losses through collision avoidance, leading to the situation that the only genuinely lost packets occur when a node wanders completely out of range of any other node, and given the scenario constraints in [5], this is not likely in our scenario until increasing separation beyond 500-600m

A significant factor of trust assessment in such a constrained environment is that there may be long periods where two edge nodes (for instance, $n0 \rightarrow n_5$) may not interact at all. This can be due to a range of factors beyond potential malicious behaviour including simple random scheduling coincidence, and intermediate or neighbouring nodes collectively causing long back-off or contention periods. This disconnection hinders and skews trust assessment in two ways; assessing nodes who do not receive timely recommendations may make decisions based on very old data, and malicious nodes have a long dwelling time where they can operate under a reasonable certainty that the TMF will not detect it (especially if it itself is performing disruptive routing attacks). One potential solution to this would be to move from a stepping-window of trust periods to a continuous trust log, updated on packet reception rather than waiting for a reasonable number of packets to arrive.

## 6   Conclusions and Future Work

We have demonstrated that existing MANET Trust Management Frameworks cannot be directly applied to the contentious and dynamic underwater medium. With significant delays (order from seconds to hours), a fading, refractive medium with varying propagation, the environment is simply not as predictable as classical MANET deployment environments.

We presented a comparison scenario between trust establishment in Terrestrial MANET and in the underwater space, demonstrating that in order to have any reasonable expectation of performance, throughput and delay responses must be characterised before implementing trust in such environments.

We demonstrated initial, unfiltered Grey Trust assessment utilising all the available metrics (transmitted and received throughput, delay, received signal strength, transmitted power, and packet loss rate) Using the knowledge that in a 'fair' environment, trust assessments should be stable about 0.5, selected THESE to continue.

We have shown that existing frameworks are overly optimistic [6] also raised the need for a more expanded view of trust but did so with a domain-partitioning approach rather than combining trust assessments from multiple domains within networks.

All the 'programming' for this bit is done, it's just writing. Remember to highlight the relationships between delay/distance/trust and RSSI/PLR trust. Also remember to show the RTS ratio for the mobility case, highlighting that when the environment is significantly more dynamic and delay tolerant, beta/otmf fail to take that into account.

select metrics

doesn't follow from rest of paragraph, needs to be expanded to explain the domain approach, possibly move back to 'future work' or something

## 7   The References Section

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# Todo list