Research Paper Presentation

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Title and Authors

Title

Maximizing the Probability of Message Delivery over Ever-changing Communication Scenarios in Tactical Networks

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Index Words

- **Ever-changing Communication scenarios**: Randomly changing communication scenarios.
- **message delivery**: It refers whether a message, which sender sends reaches receiver or not.
- **system robustness**: It refers to the ability of tolerating perturbations that might affect the system's functional body. In the same line robustness can be defined as "the ability of a system to resist change without adapting its initial stable configuration".
- **tactical networks**: Tactical networks support military operations providing the means for network-centric warfare, among military units in large areas, through heterogeneous networks combining different communication technologies, such as High Frequency (HF), Ultra High Frequency (UHF), Very High Frequency (VHF) and Satellite Communications (SatCom).

Prerequisites

- Stochastic Model
- Markov Chains
- Node
- Link
- IP packets

Stochastic Model

- A stochastic model represents a situation where uncertainty is present. In other words, it's a model for a process that has some kind of randomness. These models will likely produce different results every time the model is run.
- In this model,probabilities are assigned to events within the model and these probabilities can be used to make predictions or supply other relevant information about the process.

Markov Chains

- A Markov chain is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event.
- A Markov chain is called homogeneous, if and only if the transition probabilities are independent of time t, i.e., there exist $P_{i,j}$ such that the below equation holds for all times

$$P_{i,j} = \Pr\left(X_t = j | X_{t-1} = i\right) \tag{1}$$

Node

In telecommunications networks, a node is either a redistribution point or a communication endpoint.A physical network node is an electronic device that is attached to a network, and is capable of creating, receiving, or transmitting information over a communication channel.

Link

In a telecommunications network, a link is a communication channel that connects two or more devices for the purpose of data transmission. The link may be a dedicated physical link or a virtual circuit that uses one or more physical links or shares a physical link with other telecommunications links.

IP packets

In telecommunications and computer networking, a network packet is a formatted unit of data carried by a packet-switched network. A packet consists of control information and user data, also known as the payload. Control information provides data for delivering the payload.

Notations

Notation	Definition
$\bar{B}_m$	Identity transition matrix i for constant data rates
B_m	Transition matrix m from $\mathfrak{B}$ representing *model B*
B_{T_t}	Transformation matrix to change B
$\mathfrak{B}$	Set of transition matrices B_m for $m \in \{1,\ldots,M\}$
$\mathfrak{B}_T$	Set of transformation matrices
$\delta(t)$	Transformation step function mapping a time step t to a number of time steps from Δ
Δ	Set of number of steps for transformations between patterns
J_i	Pattern result of the *jump* i
L_i	Pattern result of the *loop* i
λ	Time distribution for state update
N	Number of states in S
$Model_B(B, \lambda)$	Stochastic model to create patterns of change in the link data rate introduced in [10]
$Model_B(B, \mathfrak{T}, \lambda)$	In-homogeneous Markov model to create patterns of change in the link data rate
p_{ij}	Conditional probability of state s_i to be chosen next given that s_j is the current state $(s_i\|s_j)$
P_i	Pendulum pattern i
ϕ_1	Update function for the state $X_t = s_i$ of a Markov chain
ϕ_2	Transformation function extending $\mathfrak{B}$ and θ to $\mathfrak{T}$
ϕ_3	Update function for the in-homogeneous model
ϕ_{sample}	Sample function to sample a sequence of states Σ
s_i	State identifier
S	Set of states of a Markov chain
σ_t	State of the experiment at time t
Σ	Sequence of states $\{\sigma_1,\ldots,\sigma_T\}$ sampled by ϕ_{sample}
$\theta(t)$	Transition matrix function mapping a time step t to the index $m \in \{1,\ldots,M\}$ of a transition matrix $B_m \in \mathfrak{B}$
$\theta_{trans}(t)$	Transformation matrix function mapping a time step t to a transformation matrix $B_{T_t}\ in \mathfrak{B}_T$
t	Point in time $\mathfrak{T}$ or $\mathfrak{T}_{init}$
τ_t	Time distribution parameter at time t, defining how long the link will stay in a state
T_i	Pattern result of the transformation i
$\mathfrak{T}$	Set of time steps $\{1,\ldots,T\}$ of an experiment
$\mathfrak{T}_{init}$	Set of initial time steps $\{1,\ldots,T\}$
x_1, x_2	Random numbers between 0 and 1
X_t	Random variable at time t
$\vec{X}_t$	Markov chain state vector at time t

Abstract

Abstract

- From its earliest days, the Army has moved through doctrine, training, and equipping the forces relying on some form of networked communications. For the most part this was an Army Signal Corps function satisfied by switches, radios, satellites, and cable.
- Therefore, tactical networks were crucial in their communication and they had to make sure that information being passed should not be affected by ever changing communication scenarios.
- So, they wanted to add an optimum redundancy to make sure that user data-flow should not be affected by packet loss, during changes in link data rate, including disconnections.
- Thus, we are going to introduce a stochastic model to maximize the probability of message delivery over ever-changing communication scenarios in tactical networks, implementing store-and-forward mechanisms organized in a hierarchy of layers for messages,IP packets and radios.

Structure of Modern Tactical Systems

- Modern tactical systems are organized into layers through multi-layer control mechanisms to handle independent changes from both user data-flows (A) and network conditions (B).
- Each node has a control plane (c) and two chains: one for incoming (i) data-flows and another for outgoing (o) data-flows, both sitting in at least four layers, namely radio (0), packet (1), message (2) and proxy/broker (3)
- The sequence of messages from (A) enter the system from layer 3 carrying a set of QoS requirements(differentiated at layer 2), which are partially mapped to IP packets at layer 1.
- The radio (layer 0) usually has a buffer with limited size that differentiates the packets by priority. Note that a multi-homed node with r radio networks will have r instances of this hierarchy of queues to handle the difference in both coverage and link data rate from military communication technologies

Ever-changing end-to-end communication scenario

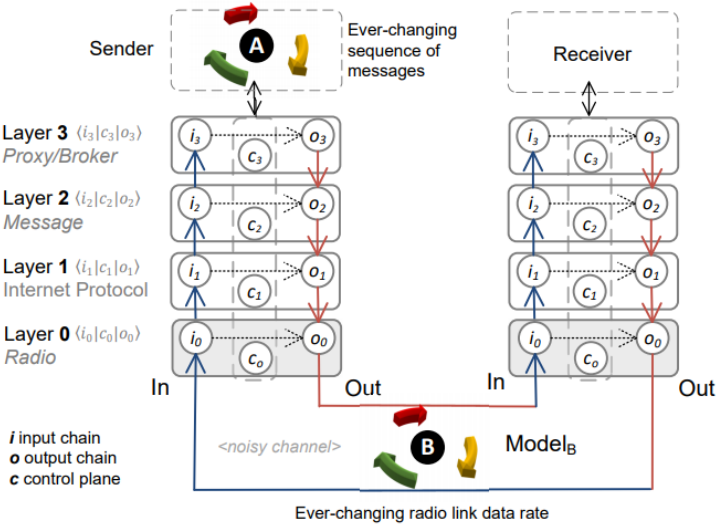

Figure: Modern tactical system model

Probability of Message delivery

- Let us assume that the network conditions in a communication scenario C is described as the five-tuple $C = (\overrightarrow{X_0}, \beta, \theta, \beta_T, \tau)$. where,
- where $\overrightarrow{X_0}$ is the initial state vector, β is a set of matrices describing M different probability distributions, θ is the update function, β_T is a set of transition matrices and τ is the time distribution of the in-homogeneous Markov model, called $Model_B$
- This stochastic model is composed of two nested Markov chains,one representing the link data rate changes and another one defining the distributions of the pattern of data rate changes(β).
- Our system implements an error correction technique called Reed Solomon Code, meaning that if the message consists of k packets and $n - k$ redundant packets, the message can be successfully delivered if at least k packets are delivered by sending a selective acknowledgement, which indicates the sequence numbers of the lost packets

Computing Probability

Assuming independent errors that might cause packet loss, the probability for the receiver getting any $0 \leq k \leq n$ out of n sent packets is given by the binomial distribution as defined in (2).

$$f_X(n; p_0; k) = \Pr(X = k) = \binom{n}{k} . p_0^k . (1 - p_0)^{n-k} \tag{2}$$

Where p_0 is the probability that a single packet will be delivered and X is a random variable measuring the number of successfully transmitted packets.

Computing Probability(contd.)

If E_1 is the event $X \geq k$, meaning that the message can be successfully delivered in the first round and E_2 is the event that the outer Markov chain of $Model_B$ is in state $s(t) = P_i$, we get

$$\Pr(E_1|E_2) = \Pr(X \geq k|s(t) = P_i) = \frac{\Pr(X \geq k, s(t) = P_i)}{\Pr(s(t) = P_i)} \tag{3}$$

This construction can be extended to compute the probability p_2 of message delivery, during a communication scenario C consisting of I different patterns $P_1 \cup ... \cup P_i \cup ... \cup P_I = C$ by finding an optimum configuration for

$$p_2 = F_{X|C}(n; p_0; k) = \Pr(X \geq k) = \sum_{i=1}^{I} \Pr(X \geq k_i|P_i) \tag{4}$$

Where the constraint $\sum_{i=1}^{I} k_i = k$ is also fulfilled at the same time.

Probability of packet delivery within a Time window

- We assume that the data rate changes of the system follow an in-homogeneous Markov chain represented by $Model_B$ with state space $\beta = B_1, ..., B_M$ resulting in a communication scenario C.
- We also assume that the distributions $B_1, ..., B_m$ together with the distribution λ are well-known and therefore we have access to an oracle knowing the link states $\Sigma = [b(1), ..., b(T)]$ at each point in time $t \in \tau = [1, ..., T]$.
- We define the function $f_l(t) = [max(0, \sum_{i=1}^{t-1} \tau_i - 1), \sum_{i=1}^{t-1} \tau_i - 1)]$ mapping a point in time $t \in \tau$ to a time interval describing how many seconds the link (inner Markov chain) stays in state $b(t) \in [0, 1, 2, 3, 4, 5]$.

Probability of packet delivery within a Time window(contd.)

Assuming the probability of delivering a packet $p_0(T_w)$ is proportional to the amount of bits received within the time window $T_w = f_l(t_1) \cup f_l(t_2)$ and the packet size is distributed by κ, the optimal data rate $b_{opt}(t)$ for almost sure delivery can be calculated using the ratio

$$b_{opt}(T_w) = \frac{\kappa}{|T_w|} \tag{5}$$

we can now compute the ratio between the current data rate $b(t)$ and the optimal data rate $b_{opt}(t)$ for arbitrary time windows T_w.

$$b_{ratio} = \frac{\sum_{t=t_1}^{t_2} \frac{f_l(t)}{|T_w|} b(t)}{b_{opt}(T_w)} \tag{6}$$

Probability of packet delivery within a Time window(contd.)

So, now we can use b_{ratio} to introduce another function $g(t, b(t), b_{opt}(T_w))$ that computes an initial guess for the probability of packet loss at layer 0.

$$g(T_w, b(t), b_{opt}(T_w)) = \begin{cases} 0, & \text{if} b(t) = 0 \forall t \in [t_1, t_2] \\ b_{ratio}, & \text{if} \sum_{t=t_1}^{t_2} \frac{f_l(t)}{|T_w|} b(t) < b_{opt}(T_w) \\ 1, & \text{if} \sum_{t=t_1}^{t_2} \frac{f_l(t)}{|T_w|} b(t) \geq b_{opt}(T_w) \end{cases} \tag{7}$$

Interpretation of function g

- If $g = 0$, then there is only one possibility which is $b(t)$ is zero for the entire time period T_w
- If $g = b_{ratio}$, then we can solve the equation, either for fixed $|T_w(t)|$ or b to adjust the system parameters such that $g = 1$ and as a result $p_0(t) > 0$.

$$\frac{|T_w(t)|.b}{\kappa} = 1 - g(t, b(t), b_{opt}(T_w)) \tag{8}$$

- If $g = 1$ and $b(t) = (1 + \epsilon).b_{opt}(t)$, then we can increase the probability of packet delivery $p_0(t)$ by adding redundancy $r(t) = \epsilon.b_{opt}(t)$. Where, $\epsilon = (b(t) - b_{opt}(t))/b_{opt}(t)$
- From the above analysis of g, we can say that

$$p_0(T_w) = \Pr(X = 1 | b(t), T_w, \kappa) \tag{9}$$

Maximising Probability of Message delivery

Let $F_{X|C}(n = r + k; p_0; k)$ be the objective function describing the binomial distribution, in (4), of successful message delivery given communication scenario C and the number of data packets k, find the optimum amount of redundancy r s.t.

$$\begin{aligned} \max_r F_{X|C}(n = r + k; p_0; k) &= \min_r 1 - F_{X|C}(n = r + k; p_0; k) \\ &= \min_r 1 - \sum_{i=1}^{I} f_{X|P_i}(n_i = r_i + k_i; p_0; k_i) \end{aligned} \quad (10)$$

Where, constraints are:

$$\sum_{i=1}^{I} k_i = k; \quad \sum_{i=1}^{I} r_i = r; \quad n_i - k_i \geq 0; \quad r_i, n_i, k_i \geq 0; \quad (11)$$

Algorithm to find optimum amount of redundancy

Algorithm 1 : MAXPROB

Input: $C = (\vec{X}_0, \mathfrak{B}, \theta, \mathfrak{B}_T, \mathfrak{T}, \lambda)$, $\mathbf{P}_0$, Msg, κ, $t_{w_{max}}$, seed

Output: Optimum amount of redundancy r,
maximized probability $\mathbb{P}(X \geq k|C)$

Initialization :

$\Sigma \leftarrow$ *Sample*($\vec{X}_0$, $\mathfrak{B}$, θ, T, λ, seed)

$S_{pt}, S_k \leftarrow []$

$p_{max}, r_{max} \leftarrow 0$

$t_w \leftarrow 1$

$k \leftarrow |\text{Msg}|$

while $t_w \leq t_{w_{max}}$ **do**

  for pattern $P_i \subseteq \Sigma$ **do**

    for k_i in $0, \ldots, k$ **do**

      Given k_i packets, compute the maximum amount of redundancy $r_i = \sum_{t=t_1}^{t_2} \epsilon \cdot b_{opt}(t)$ that the system can handle during $P_i = [b(t_1), \ldots, b(t_2)]$

      Compute the probability $\mathbb{P}(X \geq k_i|P_i)$ with redundancy $r_i = n_i - k_i = \lfloor r_i/\kappa \rfloor$ by using $p_0 \in \mathbf{P}_0$

      S_k.append$((\mathbb{P}(X \geq k_i|P_i), r_i))$

    end for

    S_{pt}.append(S_k)

  end for

  Compute the best configurations maximizing $p_{max} = \sum_{i=1}^{I}(\mathbb{P}(X \geq k_i|P_i))$, as defined in (3), s.t. $\sum_{i=1}^{I} k_i \geq k$. Keep the solution guaranteeing p_{max} with minimum amount of redundancy $r_{min} = \sum_{i=1}^{I} r_i = n_i - k_i$.

  if $p_{max} > p_{best}$ **then**

    $p_{best} \leftarrow p_{max}$

    $r_{best} \leftarrow r_{min}$

  end if

  $t_w + +$

end while

return (p_{best}, r_{best})

Figure: MAXPROB Algorithm

Theorem to prove an algorithm exists to find optimum solution

Theorem

Given a non-empty, ever-changing communication scenario $C = (\overrightarrow{X_0}, \beta, \theta, \beta_T, \tau)$, the probabilities P_0 for different end-to-end delays 1, . . . , $t_{w_{max}}$ over stable system conditions, the number $k > 0$ of data packets defining the length of a message Msg, the distribution of the the packet size κ and the maximum end-to-end delay $t_{w_{max}}$, MAXPROB computes an optimum amount of redundancy.

Proof for the theorem

Proof

We will be proving inductively that for each possible end-to-end delay $1 \leq t_w \leq t_{w_{max}}$, p_{best} is always maximized by the optimal amount of redundancy r_{best}.

Let $t_w = 1$, then lines 7-12 compute the maximum redundancy r_i and the corresponding probability $\Pr(X \geq k_i | P_i)$ by using the probabilities $p_0 \in P_0$ for each possible combination of a pattern P_i and number of packets $k_i \leq k$. The probabilities for fixed pattern Pi are stored in the data structure S_k and added to S_{pt} afterwards.In sequence (line 15), the algorithm computes all possible configurations by maximizing p_2 from (3).We keep the configuration that uses a minimum amount of redundancy r_{min}.Since $p_{max} > p_{best}$ is true, we update p_{best} and r_{best}.Thus, By line 15 r_{best} is an optimal configuration for $t_w = 1$ with probability.

The induction step $(t_w) \implies (t_w + 1)$ can be done in the same way. Since p_{best} and r_{best} are only updated if the algorithm finds a higher probability p_{max}, the tuple r_{best} is always an optimal solution. Hence, Proved.

Multi-layer Stochastic Uncertainty Model

Given the probabilities $p_i(T_w)$, $i \in Layers[0,2]$, We assume that M is an instance of $Model_B$ and that we are given the 5-tuple $C = (\overrightarrow{X_0}, \beta, \theta, \beta_T, \tau)$ required to sample the sequence by computing ϕ_{sample}. Now we can define two functions to convert the instance M to an instance U of an stochastic model describing the uncertainty of the underlying tactical system by replacing the system states of the inner Markov chain of M by probabilities p_0 and the pattern P_j representing the states of the outer Markov chain by p_2.To this end, we define the function ψ_{in} mapping each system state to a probability p_0 as

$$\psi_{in} : (s_{in}(t), t) \implies (\Pr(X = 1 | b(t) = s_{in}(t), T_w = f_l(t), \kappa)) \tag{12}$$

We can fix the state of the outer Markov chain for a time interval $[t_1, t_2]$ with $0 \leq t_1, t_2 \leq T$, meaning that the system follows a pattern $P_j = [s_{in}(t1), ..., s_{in}(t2)]$ generated by single matrix $B_j \in \beta$. Given size k of a message, we can now replace P_j by maximized probability p_2 using ψ_{out}

$$\psi_{out} : (P_j, t_1, t_2, k) \implies \Pr(X \geq k | P_i = P_j, T_w = f_l(t_1) \cup f_l(t_2), \kappa) \tag{13}$$

Experimental Results

- We used two loop patterns, L1 and L2, and the VHF network. Both patterns of change include very low link data rates (i.e 0.6 and 1.2 kbps) and even link disconnections (0 kbps) resulting in packet loss.
- Here, we demonstrate how redundancy can improve the message/packet delivery over the loop patterns L1 and L2, both with 200 states updated every 10 seconds. The messages were composed by 1, 3, 9, 18 and 54 packets, and the sender packet rate was distributed according to (0.05, 0.075, 0.1, 0.2, 0.5, 1, 2) packet/second.
- The below figure complements the results from this table by showing the probability for message delivery as a function of different time windows T_w for six messages sizes, namely 1, 3, 9, 18 and 54 packets per message. In this figure, there are two examples representing 100% (left) and 200% (right) for L1.showing that the probabilities converge with respect to the size of the maximum end-to-end delay T_w; also called time window.

Experimental Results

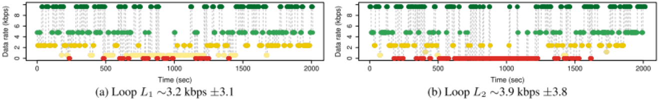

Figure: Loops L1 and L2

TABLE I: Probability of message delivery (0.2 packet/second).

C	r(t)	Number of packets per message: 1	3	9	18	54
L_1^*	0%	.69 (±.11)	.33 (±.08)	.04 (±.01)	.00 (±.00)	.00 (±.00)
L_2^*		.63 (±.09)	.25 (±.05)	.02 (±.00)	.00 (±.00)	.00 (±.00)
L_1	0%	.49 (±.11)	.30 (±.08)	.04 (±.01)	.00 (±.00)	.00 (±.00)
L_2		.61 (±.09)	.25 (±.05)	.02 (±.00)	.00 (±.00)	.00 (±.00)
L_1	100%	.69 (±.12)	.90 (±.17)	.97 (±.21)	.99 (±.24)	.99 (±.26)
L_2		.71 (±.11)	.86 (±.14)	.92 (±.18)	.96 (±.20)	.99 (±.22)
L_1	200%	.82 (±.12)	.99 (±.14)	.99 (±.16)	.99 (±.16)	.99 (±.16)
L_2		.76 (±.11)	.98 (±.14)	.99 (±.15)	.99 (±.15)	.99 (±.16)
L_1	500%	.96 (±.10)	.99 (±.12)	1.0 (±.12)	1.0 (±.13)	1.0 (±.13)
L_2		.97 (±.10)	.99 (±.11)	1.0 (±.12)	1.0 (±.12)	1.0 (±.13)

Figure: Probability of message delivery(0.2 packet/second).

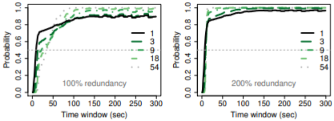

Figure: Probability as a function of the time window.

Conclusion

- This paper introduced a stochastic model to maximize the probability of message/packet delivery using the hierarchy of layers from modern tactical systems.
- The goal was to estimate the optimum redundancy level to mitigate packet loss in communication scenarios with link disconnection therefore increasing the probability of delivering messages. Thus, we started with the hypothesis that transport protocols can use our model to proactively add redundancy to reduce the packet loss observed during radio link disconnections.
- Our hypothesis was verified with experiments sending messages with different sizes through a VHF link with data rate changing in two different patterns. The experimental results suggest that our stochastic model can compute close to optimal parameters for a transport protocol using redundancy to overcome packet loss during link disconnections, also avoiding data overhead from packet acknowledgements and packet re-transmissions.

THANK YOU

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