An Energy-Efficient Architecture for Delay Tolerant Network: Optimal Control and Games Theoretic Approach

Amar Prakash Azad

INRIA Sophia Antipolis/LIA University of Avignon.

Joint work with Eitan Altman, Tamer Basar, Rachid El-Azouzi, Franceso De-Palegrini, Habib B.A. Sidi, and Julio Rojas-Mora

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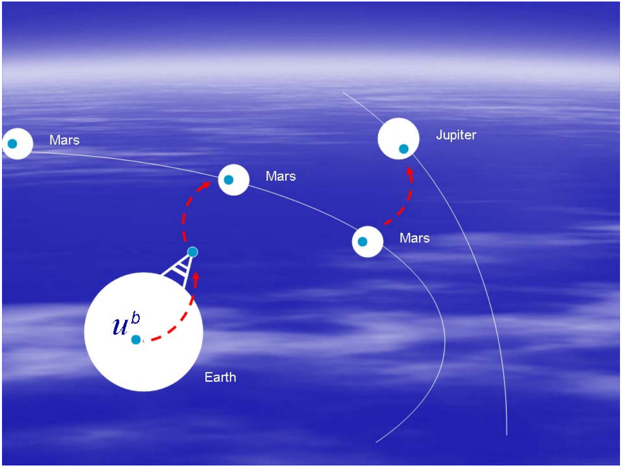
Outline

Disconnected Network

Task : Deliver message to Jupiter from Earth. How ? ?



Delay Tolerant Network ?

An approach to answer the questions raised by

- Wide Range of challenged networks,
  - No end-to-end connection exist
    - Network partitioning is frequent
    - Delay/Disruption can be tolerated
- Disseminate the communication through users at far depth.

Delay Tolerant Network
Disruption Tolerant Networking
Disconnection Tolerant Networking

Operational Overview

	Traditional	DTN
E2E Connectivity	Continuous	Frequent Disconnections

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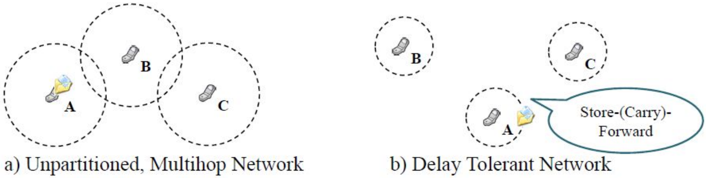

FIGURE: Contact types : Scheduled / Opportunistic / Predicted

Examples of DTNs I

1. Inter-Planet Satellite Communication Network ▸ IPN
   - InterPlaNetary Internet (IPN) ; http ://ipnsig.org/home.htm
2. Military Battlefield Network ▸ MBN
   - DTN Project @ DARPA ; http ://www.darpa.mil/sto/solicitations/DTN/
3. Energy Constrained / Sparse Wireless Sensor Networks ▸ SWSN
   - Sensor Webs Project @NASA JPL ; http ://www.jpl.nasa.gov/
4. Village Area Network ▸ VAN
   - First Mile Solutions(DakNet- MIT, Rwanda, Combodia,Costa Rica, India) ; http ://www.jpl.nasa.gov/,
   - KioskNet (VLINK)@UW ; http ://blizzard.cs.uwaterloo.ca/tetherless/index.php/KioskNet
5. Underwater Acoustic Networks ▸ UAN

Examples of DTNs II

- Underwater Acoustic Sensor Networks (UW-ASNs) Research @ GATECH ;
  http ://www.ece.gatech.edu/research/labs/bwn/UWASN
- UAN-Underwater Acoustic Network @ Europian Commission ;
  http ://www.ua-net.eu
- SiPLABoratory @ CMU,
  http ://www.siplab.fct.ualg.pt/proj/uan.shtml

6. Sparse Mobile Ad Hoc Networks ▸ SMAN
   - DOME-UMASS ; http ://prisms.cs.umass.edu/dome/
   - SARAH ; http ://www-valoria.univ-ubs.fr/SARAH
   - Haggle ; http ://www.haggleproject.org/
   - ResiliNets ; https ://wiki.ittc.ku.edu/resilinets_wiki/
   - MISUS ; http ://www.jpl.nasa.gov/
   - BIONETS ; http ://www.bionets.eu/

A Scenario

- A person is driving on a highway, carrying his own lap-top or PDA, and needs to send an email.
- There is no nearby connectivity (Base statio or access point). The user pass by other cars, buses or trains that have other people carrying similar devices.
- These users can serve as relays for the email or transaction and pass it on to others. Eventually, the message reaches someone with Internet connectivity and a direct path to the destination

DTN - Source of Delay

- Could be any combination of the following :
  - Long or Variable Propagation Delay
  - Low Node Density
    - Sparse Deployment of Nodes / Short Radio Range
  - Mobility of Nodes
  - Conserving Power
  - Low Transmission Reliability
    - Link Characteristics / Obstructions
  - Disruptions (Attack, Destruction)
- Long & variable delays
- Asymmetric data rates
- High error rates
- Consists of heterogenous networks

Challenges

Major Challenges

- Data delivery : Routing from source to destination
- Energy efficiency : Conserve energy from undesired transmissions, beaconing, etc..

Exploit the inherent properties of DTN

- Node Mobility
- Transmission control
- Signalling control

Existing Routing Schemes

Existing Routing Schemes for mobile adhoc networks can be applied to DTN.

Based on Knowledge

- No Knowledge Based - Random Mobility/Opportunistic
  - Controlled/Uncontrolled flooding
  - Coding Knowledge - Network coding/Erasure coding
- Complete Knowledge Based
  - Path Tree
  - LP (Linear Program)
- Partial Knowledge Based
  - Link Metric based
  - Probabilistic based

Flooding

- Uncontrolled Flooding
  - Epidemic Routing [A. Vahdat, 2000] [1]
    - Mobile nodes Store-(Carry)-Forward data

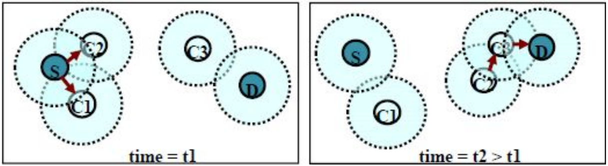

FIGURE: Store-Carry-Forward

- Controlled Flooding
  - Limit number of copies made
  - Delete obsolete messages
  - Packet dropping Policy
  - More active nodes

1. A. Vahdat and D. Becker, “Epidemic routing for partially-connected ad hoc networks, Tech. Rep. CS-2000-06, Duke University, July 2000.

Routing Strategies for DTN

- Epidemic forwarding :
  - Give a message copy to every node encountered.
  - This minimizes the delivery delay at a cost of inefficient use of network resources.
  - Generate too much transmissions
- Two hop routing protocols (Replication based routing) :
  - Source gives a copy to any relay nodes encountered
  - Relays can only give copy to destination
  - Generate less message than epidemic routing
- History-based routing
  - Keeps track record of successful delivery of nodes.

	Delivery ratio	Latency	Overhead
Epidemic	High	Low	High
Direct contact	Low	High	Low
Two hop	Medium	Medium	Medium
History-based routing	Medium (history)	Medium (history)	High

Performance Tradeoffs

Efficient Routing

- Epidemic routing : Higher the flooding, faster is the data delivery. Flooding increases redundancy. Redundancy costs in terms of system resources, e.g., Energy, Buffer memory, etc..
- Two hop routing : No flooding is resource efficient but suffers the performance due to slower delivery.

Efficient architecture requires the basic tradeoff : Routing Vs (Resource) Efficiency.

Problems and Solution Approach

- Control approach - Constrained Optimal control, Centralized decision
  - Dynamic Control of data forwarding
    - Applying Pontryagin Maximum principle - Fluid Model
    - Sample path comparison
  - Static Control of data forwarding
    - Probabilistic forwarding - With a fixed forwarding probability.
    - Optimal Forwarding switching - With a fixed time to switch the forwarding policy.
- Game approach - Individual Optimal (Node utility), Distributed decision
  - Dynamic game - ..
  - Static game
    - Population game in DTN - Fraction of nodes follows a certain forwarding strategy based on its utility/fitness function.
- Application Services Based - File version control.

Related Works : Optimal control for fluid model [2]

- N denote the total number of nodes.
- The time between contacts of any two nodes is assumed to be exponentially distributed with parameter λ
- $X(t)$ denote the infected number of nodes at time t.
- Monotone Relay strategies :
  - The number of nodes that contain the message does not decrease in time during the time t.
  - The number $X(t)$ of nodes, not including the destination, that contain the message at time t is a Markov chain.
- The goal is to maximize the delivery success probability by time τ under some constraints on the energy
- We assume that the forwarding probabilities can take any value within an interval $[u_{min}, 1]$, where $u_{min} > 0$.

Skip Details

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- We assume that the forwarding probabilities can take any value within an interval $[u_{min}, 1]$, where $u_{min} > 0$.
- Node growth dynamics is given by

$$\frac{dX(t)}{dt} = u(t)f(X(t))$$

- The delivery success probability (at u(t)=1)

Optimal Switching Strategy

Consider a model where

- A reward is given by the destination on successful delivery of packet.
- The reward is shared among nodes carrying packet.

Which routing strategy is best ?
Issues

- Epidemic routing infects the system very fast (like flooding).
- Two hop routing infects the system very slow results in low delivery probability.

Solution : Start with Epidemic routing and switch to Two hop routing.

Optimal Switching Strategy : Model

- N denote the total number of nodes.
- $X(t)$ denote the infected fraction of nodes at time t.
- s denote the switching time from epidemic to two hop routing.
- $D(t)$ denote the success probability at time t.
- $\rho = N\lambda$ denote the rate of node inter meeting.

Routing strategy

- Epidemic

$$\dot{X} = \rho X(1 - X) \Rightarrow X_1(t) = \frac{1}{1 + (N-1)e^{-\rho t}}, \quad t \leq s \qquad (1)$$

- Two hop

$$\dot{X} = \lambda(N - X) \Rightarrow X_2(t) = 1 - (1 - X_1(s))e^{-\lambda(t-s)}, \quad s > t > \tau \qquad (2)$$

Combining both with switching time s,

$$X(t, s) = X_1(t)\mathbb{1}_{[t \leq s]} + \{1 - (1 - X_1(s))e^{-\rho(t-s)}\}\mathbb{1}_{[t>s]}$$

The delivery success probability

$$D(t,s) = 1 - \exp\left(-\lambda\left(\int_0^s X_1(t) + \int_s^\tau X_2(t)dt\right)\right)$$

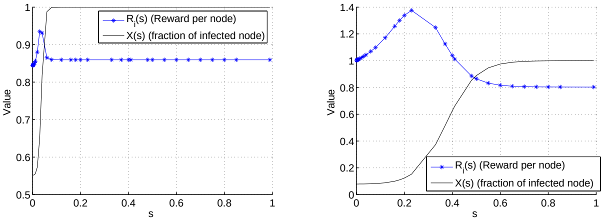
Expected Reward per node at observation time τ

$$R_i(\tau,s) = \frac{\mathbb{E}[r\mathbb{1}_{[\text{time of successful delivery}\leq\tau]}]}{X(\tau,s)} = \frac{rD(\tau,s)}{X(\tau,s)} \quad (3)$$

Optimal Switching time can be obtained

$$s^* = \operatorname*{argmax}_{0\leq s\leq\tau} R_i(s) = \operatorname*{argmax}_{0\leq s\leq\tau} \frac{R(\tau,s)}{X(\tau,s)} = \operatorname*{argmax}_{0\leq s\leq\tau} \frac{rD(\tau,s)}{X(\tau,s)} \quad (4)$$

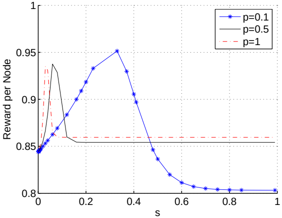
Optimal Switching



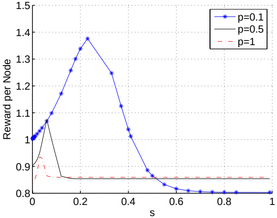
(a) probability of forwarding $u = 1$ (b) probability of forwarding $p = 0.1$

FIGURE: xaxis represents time s, yaxis represents the value $AtN = 400, \lambda = 0.4, T = 2, r = 1$.

Optimal Switching



(a) Reward per node vs Probability of forwarding



(b) Two hop routing with probability

FIGURE: xaxis represents time s, yaxis represents the value $AtN = 400, \lambda = 0.4, T = 2, r = 1$.

Energy aware control in DTN

- Energy consumption is one of the most challenging constraints for the design and implementation of DTN networks.
- The aim of this study is how mobiles, aware of their remaining energy, adjust their individual power discipline in order to maximize the delivery success probability.
- $X(t)$ is the fraction of active mobiles that have at time t copy of the message
- $Y(t)$ is the fraction of mobiles in the state ”almost dead” and having copy of the message at time t
- $Z(t)$ is the fraction of active mobiles without a copy of message at time t
- $R(t)$ is the fraction of mobiles in the state ”dead” at time time t

Energy aware control in DTN : Model

Node State dynamics

$$\frac{dX(t)}{dt} = u(t)(N - X(t) - Y(t))(\lambda - \mu)$$

$$\frac{dY(t)}{dt} = \mu u(t)(N - X(t) - Y(t))$$

Where $u(t)$ represent the mobile activity.

Utility function :

$$J(\tau) = \int_0^\tau X(t) + \beta Y(t) dt$$

Our aim is to maximize the utility function. Interpretation

- Only source node forwards the packets.
- Node has packet spend energy in listening at rate μ and reach "almost dead" state after which they can do last transmission.

Optimal dynamic Control

Theorem

Consider the problem of maximizing $J(\tau)$

(i) *a control policy is optimal if only if $u(t) = 1$ for $t \in [0, \tau]$.*

Proof : We use the Maximum principle. The Hamiltonian is

$$\begin{aligned} H(X, Y, u, p_x, p_y) &= X + \beta Y + p_x(u(N - X - Y)(\lambda - \mu)) \\ &\quad + p_y(u\mu(N - X - Y)) \end{aligned}$$

- Optimality condition is given by

$$\begin{aligned} -\dot{p}_x &= 1 - p_x u(\lambda - \mu) - p_y u\mu \\ -\dot{p}_y &= \beta - p_x(\lambda - \mu) - p_y u\mu \end{aligned}$$

Optimal dynamic Control

- Thus $\dot{p}_x = -1 + u(\lambda p_x + \mu(1-\beta)(T-t))$.
- $\frac{\partial H}{\partial u} = \frac{N-X-Y}{u}(\dot{p_x} + 1)$.
- Thus H is linear in u. Hence the the optimal control can take the two extreme values u_{min} and 1, depending on value of $\dot{p}_x$,

$$u^* = \begin{cases} u_{min}, & \text{if } \dot{p}_x < -1 \\ 1, & \text{if } \dot{p}_x \geq -1 \end{cases}$$

On careful observation one can infer from above that $\dot{p}_x$ can never be less than -1.

- Thus $u^* = 1$ for all t.

Optimal dynamic Control

With Energy Constraint Consider the problem of maximizing $J(\tau)$ subject to constraint on the energy $E(\tau) = X + Y \leq d$ where $E = (X+Y)_{u=1} > (X+Y)_{u=u_{min}}$

Proposition

$$\begin{array}{ll} E(\tau) \leq d, & \Rightarrow \; u^* = 1 \\ E(\tau) > d, & \Rightarrow \; nosolution \\ E(\tau)_{u=u_{min}} > d > E(\tau)_{u=1}, & \Rightarrow \; \text{there exist a threshold policy} \end{array}$$

Optimal dynamic Control

State Reduction

State space reduction : $M(t) = X(t) + Y(t)$ Problem,

$$
\begin{aligned}
\max_{u(t)\in[u_{min},1]} J &= \int_0^T M(t)Kdt \\
\dot{M}(t) &= u(t)\lambda(N - M(t)) \\
M(0) &= \epsilon > 0,\ M(\tau) \leq d < N
\end{aligned}
$$

where,

$$
K = \left[1 + \frac{(\beta-1)\mu(1-\epsilon)}{\lambda}\right] > 0
$$

.

Limitation : This approach is valid only when $Y(t) > 0$.

Optimal dynamic Control

Proposition

$$\begin{array}{ll} E(\tau) \le d, & \Rightarrow \; u^* = 1 \\ E(\tau) > d, & \Rightarrow \; nosolution \\ E(\tau)_{u=u_{min}} > d > E(\tau)_{u=1}, & \Rightarrow \; \textit{there exist a threshold policy} \end{array}$$

The optimal control is given by,

$$u^*(t) = \begin{cases} 1, & \text{if } 0 < t < h^* \\ u_{min}, & \text{if } h^* < t \le \tau \end{cases}$$

where the threshold is given by $h^* = \frac{\tau + \log \frac{N-d}{N-\epsilon}}{1-u_{min}}$.

Optimal dynamic Control

Proof : The Hamiltonian is

$$H(u, M, p_m) = MK + p_m u(t)(N - M). \tag{5}$$

- Linear in u, hence Bang-Bang control. There must be at least one switch.
- The co-state equation is $H_m = -\dot{p}_m(t) = K - p_m(t)u(t)$, and
  $$u(t) = \begin{cases} u_{min}, & \text{if } p_m < 0 \\ 1, & \text{if } p_m > 0 \end{cases}$$
  We use contradiction to prove. We show that if $u(0) = u_{min}$, it never switches. However if we start with $u(0) = 1$, it switches to $u(h^*) = u_{min}$ and remains there. Optimal switching time h^* can obtained by $E(\tau) = d$.

Energy aware node activation strategy in DTN

- Energy consumption is one of the most challenging constraints for the design and implementation of DTN networks.
- Here we examine how mobiles, aware of their remaining energy, adjust their individual power discipline in order to maximize the delivery success probability.
- $X(t)$ is the fraction of active mobiles that have at time t copy of the message
- $Y(t)$ is the fraction of mobiles in the state ”almost dead” and having copy of the message at time t
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Energy aware activation strategy

- we assume that the state of each mobile having packet, may take two states ”strong” (i.e., the remaining battery is greater than a threshold E_0) or ”weak” state (i.e., the remaining battery is lesser than the threshold E_0).
- Mobiles in ”strong” state, use epidemic routing, .
- Mobiles in weak state, use Two-hops routing and manage the energy consumption (activation strategy)
- Then we introduce the following standard fluid approximation (based on mean field analysis) :

$$\frac{dX(t)}{dt} = \lambda X(t)Z(t) - \mu X(t)Z(t) - \mu_1 X(t)$$

$$\frac{dY(t)}{dt} = \mu X(t)Z(t) + \mu_1 X(t) - \mu_1 u_t Y(t)$$

$$\frac{dZ(t)}{dt} = -\lambda X(t)Z(t)$$

Energy aware activation strategy

- The probability of successful delivery of the message by time τ is

$$D_i(\tau) = 1 - \exp\left(- \lambda \int_0^{\tau} (X(t) + Y(t)u(t))dt \right) \quad (6)$$

- Theorem : Consider the problem of maximizing $D(\tau)$. Then a control policy u is optimal if and only if $u(t) = 1$ for $t \in [0, \tau]$.

Optimal dynamic control

Proof. We use the Maximum Principle. The Hamiltonian is

$$H(X,Y,Z,u,p_X,p_Y,p_Z,\beta) = X + Yu + p_X(XZ - \mu XZ - \mu_1 X) + p_Y(XZ - \mu_1 X - \mu_1 uY) - p_Z \lambda XZ$$

- The optimality condition is given by

$$\frac{\partial H}{\partial u} = Y(1-\beta-p_Y\mu_1) = \begin{cases} >0 & \text{if } u^* = 1 \\ <0 & \text{if } u^* = u_{min} \end{cases}$$

$$\frac{\partial H}{\partial Y} = -\dot{p}_Y = u(1-\beta-p_Y\mu_1)$$

- Thus $\frac{\partial H}{\partial Y} = -\frac{Y\dot{p}_y}{u}$.
- H is linear in u. Hence the optimal control takes the two extreme values u_{min} and 1, depending on whether the derivative of p_Y, is negative or positive

$$u(t) = \begin{cases} u_{min} & \text{if } \dot{p_Y} > 0 \\ 1 & \text{if } \dot{p_Y} < 0 \end{cases}$$

Optimal dynamic control

- The solution of differential equation (7) is given by Thus

$$\dot{p}_Y(t) = -u(t)\exp(-\mu \int_t^T u(s)ds)) \tag{7}$$

- It follow from the last equation that $\dot{p}_Y(t)$ is negative and the optimal solution is $u^* = 1$ for all t.

Population Class Games in DTN

- A mobile selects to join one of the class
  - Epidemic routing class - N_e
  - Two hop routing class - N_t
- Total number of mobile at time 0 is

$$N_{tot} = N^0 + N_e^0 + N_t^0$$

.

- Probability of successful delivery of packet is

$$P_{succ}(\tau) = 1 - \exp(-\lambda \int_0^{\tau} (X_e(t) + X_t(t))dt)$$

Basic assumptions

- No feedback is assumed
- Message is useful only till time τ

DTN Population Game framework

Reward and Utility

- A reward α is obtained on a successful delivery.
- Amount α_e is shared among epidemic nodes having the packet and α_t is shared among two hop nodes.

$$\alpha = \alpha_e + \alpha_t.$$

- Utility function for users are given by
  - Epidemic Users

$$U_e(N_e) = \frac{\alpha_e P_{succ}(\tau)}{X_e(\tau)} - \beta\tau, \quad \text{where} \beta \text{ is the energy cost}$$

  - Two hop users

$$U_t(N_t) = \frac{\alpha_t P_{succ}(\tau)}{X_e(\tau)} - \gamma\tau, \quad \text{where} \gamma \text{ is the energy cost}$$

Solutions with fluid approximation

Fluid Approximation

$$\begin{aligned}\dot{X}_e &= (\lambda_s + \lambda X_e)(N_e - X_e)\\ \dot{X}_t &= (\lambda_s + \lambda X_t)(N_t - X_t)\end{aligned}$$

Solving with initial conditions $X_e(0) = 0, X_t(0) = 0$, we get

$$X_e(t, N_e) = \frac{\lambda_s(N_e + N_e^0)(1 - e^{-t(\lambda_s+\lambda(N_e+N_e^0))})}{\lambda_s + (N_e + N_e^0)\lambda e^{-t(\lambda_s+\lambda(N_e+N_e^0))}}$$

$$X_t(t, N_e) = \frac{\lambda_s(N - N_e + N_e^0)(1 - e^{-t(\lambda_s+\lambda(N_e))})}{\lambda_s + (N_e + N_e^0)\lambda e^{-t(\lambda_s+\lambda(N_e+N_e^0))}}$$

Combining both we get

$$\begin{aligned}X(t) &= X_e(t, N_e) + X_t(t, N_e)\\ &= \frac{\lambda_s(N + N_e^0 + N_t^0)(1 - e^{-t(\lambda_s+\lambda(N_e+N_e^0))})}{\lambda_s + (N_e + N_e^0)\lambda e^{-t(\lambda_s+\lambda(N_e+N_e^0))}}\end{aligned}$$

Stochastic approximation algorithm to converge on Nash equilibrium

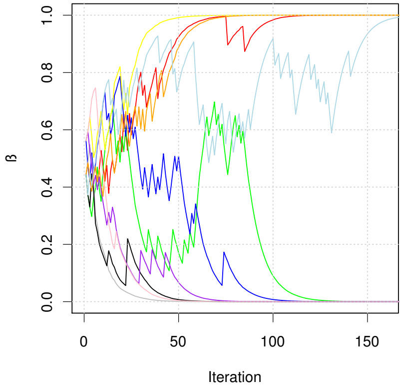


FIGURE: Converging to pure Nash equilibrium

Population Class Games in DTN

- Game problem : (N_e^*, N_t^*) is the Nash Equilibrium only iff

$$\begin{aligned} U_e(N_e^*) &\geq U_t(N_e^* - 1) \\ U_t(N_e^*) &\geq U_e(N_e^* + 1) \end{aligned}$$

On Going work

On going directions

- Dynamic configuration :
  - Arrival of new mobiles in the system.
  - Limited duration of activation.
- The right pricing scheme that drives the system to be energy efficient at Nash equilibrium as close as possible to that of the optimal partition.

Optimal Activation and Transmission Control

Consider a two hop scenario. Energy is mainly consumed in beaconing [3] (rather then transmission of packet).

- Mobiles are made active Only when required. why ?
  - An active mobile consumes energy in beaconing. Hence may die before required.
- Dynamic activation control policy is allowed which controls the active duration of each mobile.
- Mobile nodes send beacons to discover source node untill they receive the packet.
- Nodes once receive a packet do not spend energy in beaconing. Therefore, we assume that only fresh nodes die.

3. Beaconing helps to search the source faster.

Model

- # of mobiles nodes : $N+1$
- Mobility : Random Way point
- # of infected nodes : $X(t)$
- # of fresh nodes : $Y(t)$
- Node intermeeting rate : ζ
- Death rate due to beaconing : μ
- Activation rate is upper bounded by $K(t)$.

States and Control

- State of Mobile
  i. *inactive* : the tagged node does not take part in any communication ;
  ii. *activated* : the tagged node does not have a message copy, it keeps beaconing until it receives a message copy ;
  iii. *infected* : a node with a message is active but it does not send beacons.
- Control
  a. *activation rate control* $V(.)$: inactive mobiles do not contribute to communications in the DTN and do not use energy. By activating less/more mobiles per unit of time, one can use resources when needed.
  b. *transmission control* $U(.)$: the beaconing transmission power is controlled in order to mitigate the battery discharge of active relay nodes.

Dynamic Equation

- Evolution rule (Fluid approximation)
  - $X(t)$ grows at a rate given by the following pair of coupled differential equations :

$$\dot{X}(t) = U(t)Y(t)\xi \quad (8)$$

$$\dot{Y}(t) = -U(t)Y(t)(\xi + \mu) + V(t) \quad (9)$$

- Delivery Delay Distribution T_d
  $\mathcal{D}(t) := P(T_d < t)$ is given by (see (Small & Haas, 2003, Appendix A)),

$$\mathcal{D}(t) = 1 - (1 - z)\exp\Big(- N\xi \int_{s=0}^{t} X(s)ds\Big), \quad (10)$$

Note that because of monotonicity, maximizing $\mathcal{D}(t)$ is equivalent to maximizing $\int_{s=0}^{t} X(s)ds$.

Beaconing and Energy Consumption

- Energy is consumed in
  - Transmission - Only once due to "Two Hop", thus not very important.
  - Beaconing - Untill the packet is recieved, to search the source.
- Total energy consumed in beaconing during $[0, T]$ is

$$\mu \int_0^T U(s)Y(s)ds = \frac{\mu}{\xi}(X(T) - X(0))$$

Remark

The total energy consumed for transmission and reception during $[0, T]$ *is* $\epsilon(X(T) - X(0))$.

Problem Formulation

Our goal is to obtain *joint optimal* policies for the activation $V(t)$ and the transmission control $U(t)$, with $U(t) \in [u, 1]$, and $V(\cdot)$ satisfying the additional upper-bound and integral constraints introduced earlier, that solve

$$\max_{\{V(\cdot)\in\mathcal{V}, U(\cdot)\}} \mathcal{D}(T), \quad \text{s.t.} \quad X(T) \leq x, X(0) = z\,, \tag{11}$$

where x and z ($x > z$) are specified.

Recall that maximizing $\mathcal{D}(T)$ is equivalent to maximizing $\int_0^T X(t)dt$.

Optimal Control

Earlier approaches were based on

- Pontryagin maximum principle in (Altman, Başar, & De Pellegrini, 2008),
- Sample path comparisons(Altman, Neglia, Pellegrini, & Miorandi, 2009), and, some on stochastic ordering.

These approaches, developed in the context of DTNs with one type of population, are not applicable here.

Optimization

- :(Decoupling of controls is not possible.
- :) Follow two step optimization :

Step1 : Hold $U(t) \in [u, 1]$ fixed, carry out optimization with respect to $V(\cdot)$.

Step2 : Substitute $V^*(\cdot)$, back into the objective function and carry out a further maximization with respect to $U^*(\cdot)$.

- Express the objective function as follows

$$\int_0^T X(t)dt = \xi \int_0^T m(t)V(t)dt \, , \tag{12}$$

It turns out that $m(t)$ is linear.

Optimal Activation Control

Lemma

$$\int_0^T X(t)dt = \xi \int_0^T m(t)V(t)dt\,, \tag{13}$$

holds where, $m(t)$ is a linear function. Proof

Lemma

$m(t)$ is non-increasing in t for all $U(\cdot) \geq 0$, and is monotonically decreasing for $U(t) > 0$.

Optimal Activation Control

Lemma

$$\int_0^T X(t)dt = \xi \int_0^T m(t)V(t)dt\,, \tag{13}$$

holds where, $m(t)$ is a linear function. Proof

Lemma

$m(t)$ is non-increasing in t for all $U(\cdot) \geq 0$, and is monotonically decreasing for $U(t) > 0$. Moreover, the expression for $m(\cdot)$, as given in (25), can equivalently be written as

$$m(t) = \int_t^T (T-s)U(s)\Phi(s,0)ds\Phi(0,t) \tag{14}$$

Proof

Optimal Activation Policy

Theorem

The optimal policy V^* exists and is given by ▸ Proof

$$V^*(t) = \begin{cases} K(t) & \text{if } 0 \le t \le \ell, \\ 0 & \text{otherwise} \end{cases}. \quad (15)$$

In other words V^* is a threshold policy.

Corollary

Let $\int_0^\delta V(s)ds > 0$ for any $\delta > 0$. Then,

$$Y(t) > 0, \ \forall t > 0 \quad (16)$$

Also, $X(t)$ is a non-decreasing function for all $t > 0$, and monotone increasing function when $U(t)$ is strictly positive.

Recall that $\dot{X}(t) = U(t)Y(t)\xi$.

Optimal Activation

(*Turnpike property*) We note from Theorem 2 that for all T large enough (in fact for all T that satisfy $\int_0^T K(s)ds \geq 1$), the optimal threshold ℓ is the same.

Transmission Control

For any given activation policy V, we obtain a single differential equation which is equivalent to the original system, i.e.,

$$\dot{X} = U(t)\xi g(X,t) \quad (17)$$

where $g(X,t) := (f(t) - X(t))^{\frac{\xi+\mu}{\xi}}$, and $f(t) := \frac{\xi}{\xi+\mu} \int_0^t V(s)ds + z$.

Skip proof

Transmission Control

For any given activation policy V, we obtain a single differential equation which is equivalent to the original system, i.e.,

$$\dot{X} = U(t)\xi g(X,t) \tag{17}$$

where $g(X,t) := (f(t) - X(t))^{\frac{\xi+\mu}{\xi}}$, and $f(t) := \frac{\xi}{\xi+\mu}\int_0^t V(s)ds + z$.

Démonstration.

From (8) and (9) we have

$$\begin{aligned}
&\dot{X}(t) + \frac{\xi}{\xi+\mu}\dot{Y}(t) = \frac{\xi}{\xi+\mu}V(t) \\
&\Rightarrow X(t) + Y(t)\frac{\xi}{\xi+\mu} = \frac{\xi}{\xi+\mu}\int_0^t V(s)ds + z \\
&\Rightarrow Y(t) = (f(t) - X(t))\frac{\xi+\mu}{\xi}
\end{aligned} \tag{18}$$

where we introduced $f(t) := \frac{\xi}{\xi+\mu}\int_0^t V(s)ds + z$, which depends only on the activation control.

Transmission Control

Uncontrolled Dynamics, i.e., $U(t) = 1$

Proposition

For a given activation policy V, the fraction of infected nodes under uncontrolled dynamics and initial condition ($X(0) = z$) is

$$\overline{X}(t) = \frac{\xi}{\xi + \mu} \int_0^t (1 - e^{-(\xi+\mu)(t-s)}) V(s) ds + z \qquad (19)$$

Optimal Transmission Control

Definition

A policy U restricted to take values in $[u, 1]$ is called a threshold policy with parameter h if $U(t) = 1$ for $t \leq h$ a.e. and $U(t) = u$ for $t > h$ a.e..

Optimal Transmission Control

Yet another threshold policy.

Theorem

Consider the problem of maximizing $\mathcal{D}(T)$ with respect to $U(\cdot)$ subject to the constraint $X(T) \leq z + x$, under the activation control V.

i. *If $\overline{X}(T) \leq x + z$, then the optimal policy is $U(t) = 1$.*

ii. *If $\overline{X}(uT) > x + z$, then there is no feasible solution.*

iii. *If $\overline{X}(T) > x + z > \overline{X}(uT)$, then there exists a threshold policy. An optimal policy is necessarily a threshold one in the form*

$$U^*(t) = \begin{cases} 1 & \text{if } t \leq h^* \\ u & \text{if } t > h^* \end{cases} \tag{20}$$

Activation and Transmission Threshold

Theorem

If $T > \max\{h^*, \ell\}$, then the following relation holds for the bound x and the threshold h^* :

$$\begin{aligned} h^* &> \ell, \quad \text{if } x > \overline{X}(\ell) + \Delta X(\ell, T), \\ h^* &\le \ell, \quad \text{otherwise}, \end{aligned} \tag{21}$$

where

$$\begin{aligned} \overline{X}(\ell) &= \frac{\xi}{\xi+\mu} \int_0^{\ell} (1 - e^{-(\xi+\mu)(\ell-s)}) V(s) ds, \\ \Delta X(\ell, T) &= \left(\frac{\xi}{\xi+\mu} - \overline{X}(\ell) \right) \left(1 - e^{-u(\xi+\mu)(T-\ell)}\right). \end{aligned}$$

$\overline{X}(\ell)$ denotes the uncontrolled growth of X in $t = (0, \ell]$ and $\Delta X(\ell, T)$ refers to the increment in X in $(\ell, T]$ under the controlled dynamics (with $U = u$).

Activation and Transmission Threshold I

Moreover, when both threshold times coincide, i.e. $h^* = \ell$, the bound x can be expressed as

$$x = X(T) = \overline{X}(\ell) + \frac{\xi}{\xi + \mu}(1 - e^{-u(\xi+\mu)(T-\ell)}).$$

Activation Examples

Activation Schemes

- Uniform activation : $K_0 = 1/\ell$
- Linear activation : $K_0 = 2/\ell^2$
- Exponential activation : $K_0 = \alpha/(\exp(\alpha\ell) - 1)$.

Uniform Activation

Proposition

The optimal threshold for constant activation is given by

$$h^* = \begin{cases} \min(\hat{t}, T), & \textit{if } x > \overline{X}(\ell) \ (h^* > \ell) \\ \min(\tilde{t}, T), & \textit{if } x \leq \overline{X}(\ell) \ (h^* \leq \ell) \end{cases} \quad (22)$$

where,

$$\hat{t} = \frac{1}{\xi+\mu} \log \frac{\xi(e^{(\xi+\mu)\ell} - 1)}{(\xi+\mu)^2 \ell (x - \frac{\xi}{\xi+\mu})},$$

$$\tilde{t} = \frac{L(-e^{-(x\ell(\xi+\mu)^2+\xi)/\xi})\xi + x\ell(\xi+\mu)^2 + \xi}{\xi(\xi+\mu)}.$$

Here $L(\cdot)$ denotes the Lambert function, [a] *which is real-valued on the interval $[-\exp(-1), 0]$ and always below -1.*

a. The *Lambert function*, satisfies $L(x)\exp(L(x)) = x$. As the equation $y\exp(y) = x$ has an infinite number of solutions y for each (non-zero) value of x, the function $L(x)$ has an infinite number of branches.

Impact of time horizon T

Define $\underline{T}_m := sup\{t : \underline{X}(t) \leq x\}$ and $\overline{T}_m := sup\{t : \overline{X}(t) \leq x\}$.

Proposition

Consider maximization of $\mathcal{D}(T)$ subject to the constraint $X(T) \leq z + x$, under the optimal activation control V^* and transmission control $U(t) \in [u, 1]$.

i. *For $u > 0$, there is no feasible policy for any $T > \underline{T}_m$.*

ii. *For $u = 0$, the optimal transmission policy when $T \to \infty$ is given by,*

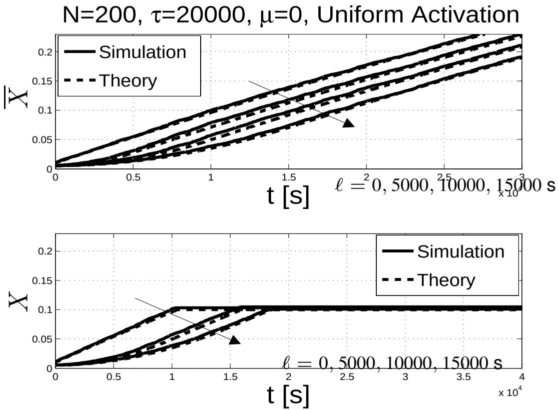
$$A^* = \begin{cases} U(t) = 1 & \text{if } t \leq \overline{T}_m \\ U(t) = 0 & \text{if } t > \overline{T}_m. \end{cases} \tag{23}$$

Numerical Validation

Simulation setting

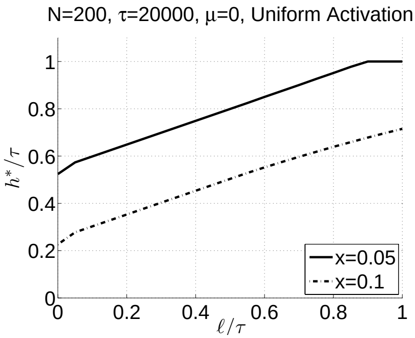
- Simulation Method : Trace based with Matlab Script. Steady state capturing.
- Mobility : Random Waypoint (RWP) model, $v = 4.2m/s$.
- Region parameters : Square region with 5kms side. $N = 200$.
- Communication range : R=15m.

Numerical Validation I



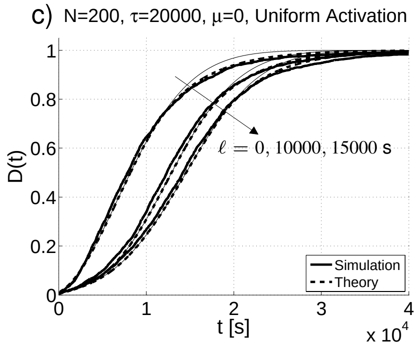
(a) Dynamics of the number of infected nodes under uniform activation, when $\ell = 0, 5000, 10000, 15000$; upper part (a.I) depicts uncontrolled dynamics, the lower one (a.II) optimal dynamics for $x = 0.1$. Earlier the activation, more the infection and quicker the saturation.

Numerical Validation II



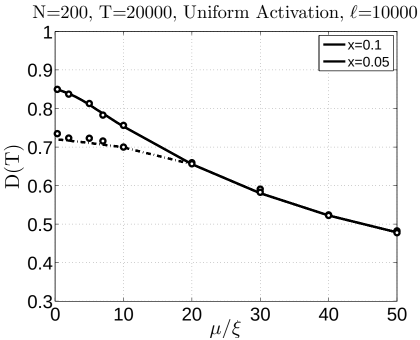
(b) Optimal Threshold under constant activation for two different values of x.

Numerical Validation III



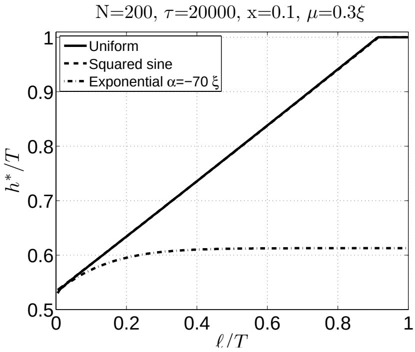
(c) CDF of the delay for optimal control : the thin solid lines represent the value attained by the uncontrolled dynamics. The case $\ell = 0$ corresponds to plain Two hops routing.

Numerical Validation IV



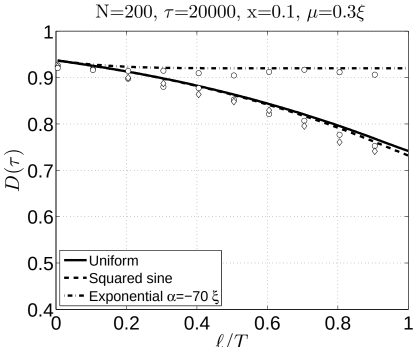
(d) Success probability for increasing values of μ/ξ, under uniform activation with $\ell = 10000$ s and $x+z = 0.05, 0.1$, respectively.

Numerical Validation I



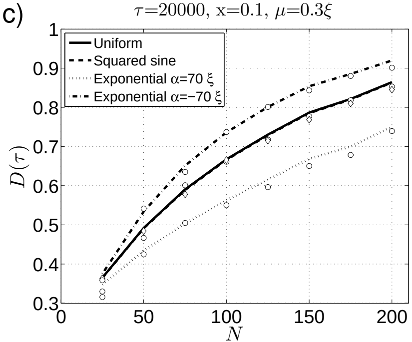
(e) Optimal threshold as a function of ℓ

Numerical Validation II



(f) Corresponding success probability $\mathcal{D}(T)$

Numerical Validation III



(g) Success probability for increasing number of nodes. Different lines refer to the case of uniform (solid), squared sine and truncated exponential activation bounds

Concluding Remarks

- Devised a new method that is based on identifying the exact weight of the activation control at each time instant.
- Validated our theoretical results through simulations for various activation schemes or constraints on activation.
- Note that we could have formulated the problem with soft constraints, instead of hard constraints, using a weighted sum of throughput and energy cost.

References I

Altman, E., Başar, T., & De Pellegrini, F. (2008, October 24). Optimal monotone forwarding policies in delay tolerant mobile ad-hoc networks. In *Proc. of acm/icst inter-perf.* Athens, Greece : ACM.

Altman, E., Neglia, G., Pellegrini, F. D., & Miorandi, D. (2009). Decentralized stochastic control of delay tolerant networks. In *Proc. of infocom.*

Small, T., & Haas, Z. J. (2003). The shared wireless infostation model : a new ad hoc networking paradigm (or where there is a whale, there is a way). In *in proc. of mobihoc* (pp. 233–244). New York : ACM.

Thanks

Questions ?

IPN

Inter-Planet Satellite Communication Network [4] [5]

- Internet Service in Space (Initial concept of DTN)
- Characteristics
  - High Intermittent Connectivity
  - Extremely Long Propagation Delay : finite speed of light
  - Low Transmission Reliability : positioning inaccuracy, limited visibility.
  - Low, Asymmetric Data Rate
- Current Projects
  - InterPlaNetary Internet (IPN)
    - DARPA, NASA JPL, MITRE, USC, UCLA, CalTech, etc.

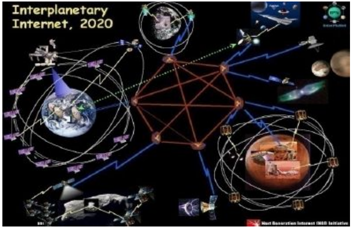


FIGURE: Future Internet

Back

4. http ://ipnsig.org/home.htm
5. http ://www.spectrum.ieee.org/telecom/internet/interplanetary-internet-tested

Military Battlefield Network [6]

- No consistent network infrastructure and frequent disruptions
- Characteristics
  - High Intermittent Connectivity
  - Mobility, destruction, noise, attack, interference
  - Low Transmission Reliability : positioning inaccuracy, limited visibility.
  - Low, Data Rate
- Current Projects
  - DTN Project @ DARPA

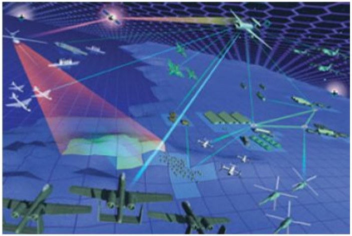


FIGURE: Electronic Military Battle

Back

6. http ://www.darpa.mil/sto/solicitations/DTN/

Energy Constrained Sparse Wireless Sensor Networks [7]

- Coordinating the activities of multiple sensors to monitor science and hazard events
- Space, terrestrial, and airborne
- Characteristics
  - Intermittent Connectivity
  - Power saving, sparse deployment
  - Low, Asymmetric Data Rate
- Current Projects
  - Sensor Webs Project @ NASA JPL

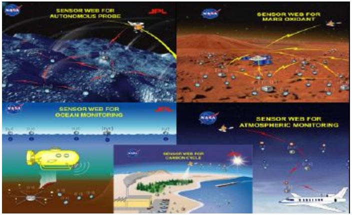


FIGURE: Interconnecting Various Networks

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7. http ://www.jpl.nasa.gov/

VAN

Village Area Network

- Asynchronous digital connectivity in rural areas by transportation systems
- Characteristics
  - Intermittent Connectivity
  - Mobility, sparse deployment
  - High Propagation Delay : transportation speed
  - Asymmetric Data Rate : heterogeneous
- Current Projects
  - First Mile Solutions [a]
    - Commercialization of DakNet (MIT)
    - Rwanda, Cambodia, Costa Rica, India

a. http ://www.firstmilesolutions.com/

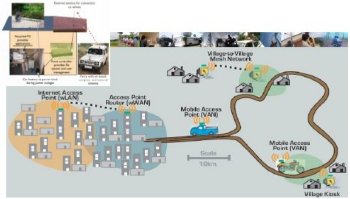

FIGURE: Remote Connectivity (affordable)

Back

- KioskNet (VLINK)UW [a]

a. http ://blizzard.cs.uwaterloo.ca/tetherless/index.ph

UAN

Underwater Acoustic Networks

- Environmental Monitoring, Disaster Prevention, Assisted Navigation
- Characteristics
  - Intermittent Connectivity
  - Mobility, sparse deployment
  - High propagation delay :1.5Km/s
  - Transmission Reliability : positioning inaccuracy, high attenuation
  - High transmission cost
  - Low asymmetric data Rate
- Current Projects
  - Underwater Acoustic Sensor Networks (UW-ASNs) Research @ GATECH [a]

a. http ://www.ece.gatech.edu/research/labs/bwn/UWASN

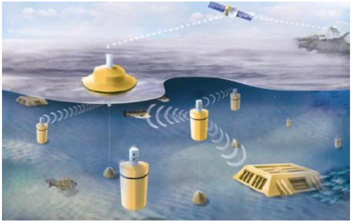

FIGURE: Underwater connectivity

Back

- UAN - Underwater Acoustic Network @ European Commission [a]
- SiPLABoratory @ CMU [b]

a. http ://www.ua-net.eu
b. http ://www.siplab.fct.ualg.pt/proj/ua

SMAN

Sparse Mobile Ad Hoc Networks

- Intermittent Autonomous, Opportunistic Communication, Assisted Navigation
- Characteristics
  - Intermittent Connectivity
  - Mobility, sparse deployment
  - Large E2E delay
- Current Projects
  - **DOME** : Diverse Outdoor Mobile Environment @ UMass [a]
  - **SARAH** @ Agence Nationale de la Recherche [b]
  - Haggle Project @ European Union Framework Program [c]

a. http ://prisms.cs.umass.edu/dome/
b. http ://www-valoria.univ-ubs.fr/SARAH/
c. http ://www.haggleproject.org/

FIGURE: Spars Network Adhoc connectivity

Back

- **ResiliNets** : Resilient and Survivable Networks @ KU [a]
- **MISUS** (Multi-Rover Integrated Science Understanding System)@ NASA JPL [b]

a. https ://wiki.ittc.ku.edu/resilinets_wi

Optimal Activation Control

Lemma

$$\int_0^T X(t)dt = \xi \int_0^T m(t)V(t)dt\,, \quad (24)$$

holds where,

$$\begin{aligned} m(t) \quad &= \quad Z(T)\Phi(0,t) - Z(t)\Phi(0,t) \\ &\quad -TW(t)\Phi(0,t) + tW(t)\Phi(0,t) \end{aligned} \quad (25)$$

and $\Phi(t,T) = \exp\left(-(\xi+\mu)\int_T^t U(s)ds\right)$*, and,*
letting $dW := U(\sigma)\Phi(\sigma,0)d\sigma$*, and,*
defining $dZ = W(t)dt$*.*

Return

Optimal Activation Control

$$Z(t) = tW(t) - \int_0^t sU(s)\Phi(s,0)ds$$

$$\text{Thus,} \quad m(t) = \int_t^T (T-s)U(s)\Phi(s,0)ds\Phi(0,t) \qquad (26)$$

$$\text{where} \quad \Phi(s,0) = \exp\left(-\int_0^s U(s)ds\right)$$

Since $\Phi(t,0)\Phi(0,t) = 1$, and

$$\frac{d}{dt}\Phi(0,t) = (\xi+\mu)U(t)\Phi(0,t)\,,$$

we obtain

$$\frac{dm(t)}{dt} = -(T-t)U(t) - (\xi+\mu)U(t)m(t)\,,$$

which is non-positive for all $t \in [0,T]$ since $m(t)$ is nonnegative, and is strictly negative whenever $U(t) > 0$.

◀ Return

Optimal Activation Policy

Theorem

The optimal policy V^* exists and is given by

$$V^*(t) = \begin{cases} K(t) & \text{if } 0 \leq t \leq \ell, \\ 0 & \text{otherwise} \end{cases}. \tag{27}$$

Proof: Any activation policy V can be viewed as a probability measure over $[0, T]$; let us call Q^* and Q two random variables having density V^* and V respectively, where V^* is defined in eq. (27), and where V is an arbitrary other policy. By construction, $\mathbb{P}[Q > t] \geq \mathbb{P}[Q^* > t]$. Since m is continuous, for $t \in I = m([0, T])$ we can define $\underline{t} = \min(m^{-1}(t))$ so that

$$\mathbb{P}[m(Q^*) > t] = \mathbb{P}[Q^* \leq \underline{t}] \geq \mathbb{P}[Q \leq \underline{t}] = \mathbb{P}[m(Q) > t]$$

which concludes the proof since $\mathbb{E}m(Q^*) \geq \mathbb{E}m(Q)$. $\diamondsuit$

Return