# TIME LATENCY OF INFORMATION IN NETWORKED OPERATIONS: EFFECT OF 'HUMAN IN THE LOOP'

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## ABSTRACT

Time has always been of crucial importance in military networked operations, and consequently of Command and Control. Often, humans are required to extract, interpret and validate information from raw data at one or more points along the path from source to users. In this paper, we study the time latency of information under the influence of 'human in the loop' in networked operations, using the Canadian Forces Intelligence unit as an illustrative example. We derive a closed form expression for the time delay associated with human interpretation of data via a Discrete Time Markov Chain model. Parametric studies on changes in the governing variables of the time delay expression provide us with valuable insights on how to expedite the filtering, analyzing and redirecting of information process through training. The aim is to better understand the issues on 'timeliness' of information.

Key Words: Time latency, Command and control, networked enabled operations, Discrete Time Markov Chain

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## INTRODUCTION

The Network centric warfare (NCW) and the less ambitious model of network enabled operations (NEO) proposed in the late 1990s has been regarded as one of the defining trends in the development of military systems and capabilities [1]. Its aim is to improve situation awareness and accelerate the 'observation-orientation-decision-action (OODA) loop' [2] by using the network to rapidly gather and distribute information. While much literature exists which extols the virtues of NCW/NEO, however, there are risks associated with NCW/NEO. For example, NEO depends heavily on technology and may be vulnerable to asymmetric attack. Additionally, network operations frequently involve human participations and/or interventions. As such, human influence on the performance of network operations has to be explored and assessed.

In military networked operations, humans are often required to extract, interpret and validate (machine) information from raw data at one or more points along the path from source to users. Information is not the same as raw data. Often, raw data must be understood and interpreted by humans to produce information. The effect of 'human in the loop' is further witnessed by the fact that no military force globally can, for both ethical and legal reasons, adopt a policy which permits fully autonomous detection, acquisition, tracking and weapon delivery against a target by a machine. Ultimately, human beings still control the final decision such as on whether or not to fire a weapon against a target. In networked operations then, the human introduces a necessary but significant delay in the path from source to users. In this paper, we will study this time latency of information caused by the presence of 'human in the loop' in networked operations.

In brief, time latency in networked operations is the sum of average message (transmission, queuing and propagation) delay together with the time required for quality evaluation of human operator activities in interpreting information. The modeling of transmission and queuing delay for packets in communication nets is generally based on the *M/M/1* queue and its variants, Kleinrock's *Independence Assumption* [3] and Burke's Theorem [4]. As a consequence, Jackson's open queuing network results [5]. Details on the transmission, queuing formulation and solution can be found in [3, 6]. Our emphasis in this paper is to gauge the time delay caused by the presence of humans in filtering, analyzing and redirecting information in military networked operations.

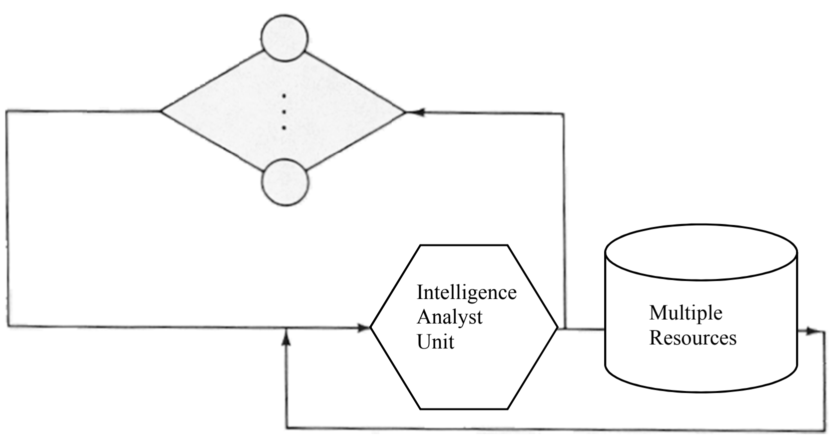
Time has always been of critical importance in military networked operations and combat. In a typical discussion of Command and Control, it is taken as axiomatic that the information presented to the commander must be timely as well as accurate and complete [7]. Timeliness is the degree to which mission performance depends on timely and perhaps perishable information [8]. On the other hand, accuracy and completeness refers to information quality. Completeness of information implies that it is relevant, comprehensive, sufficient and/or adequate. In this paper, we derive the time delay associated with human interpretation of data via a Discrete Time Markov Chain (DTMC) model and then using symbolic computations, we compute a closed form solution for the time latency. The closed form solution, a salient feature of symbolic computations, enables us to easily conduct parametric studies on changes in the governing variables [9]. It provides us with valuable insights on how to expedite the filtration, analysis and redirection of information process through training. The aim of our study is to suggest means to reduce time latency of information under the influence of 'human in the loop' and thus is one step closer towards understanding timeliness of information.

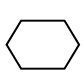
To better illustrate our modeling approach, we present our analysis through a generic discussion on a typical Canadian Forces (CF) Intelligence cell. In the Markov Model, the various states are representations of the different courses of action corresponding to the status of human perception towards the completeness of existing information in the intelligence database. (An intelligence database can include well-structured format data ready for information processing to various collections of interview notes, maps, documents on the requested topic, etc.) Upon receiving tasking from customer, the intelligence analyst will initially assess whether the information in the existing intelligence database contains sufficient, relevant and comprehensive (complete) information to analyze the tasking. If not, appropriate actions to request supplementary information from other agencies will be taken. The different courses of action correspond to the correctness in the deduction of completeness of information in the existing database by the analyst. The current mathematical model does not address information accuracy. Information accuracy is difficult to gauge a-priori and can be verified only after the fact. For example, consider the case where an analyst is tasked to ascertain whether country Y possesses chemical weapons. The analyst may consider complete information to include aerial pictures of suspected locations, remote sensing of chemical agents etc. However, the accuracy of the information from these sources can only be verified by an actual search of the suspected locations.

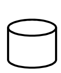
The paper is organized as follows. First, we will briefly outline the operations procedure within the CF intelligence cell. We will formulate the Discrete Time Markov Chain for the information flow; derive the closed form solution using well-established results in absorbing Markov Chain; and provide insights on reducing the time latency of information through training. Finally, data collected on operations within the Intelligence cell is analyzed to highlight the approach.

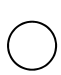
<u>BACKGROUND</u>

In essence, a typical intelligence unit within the Canadian Forces resembles an information processing center where its primary function is the *timel*y fusion of *complete (possible incomplete)* information. Initially, CF customers request analysis via the intelligence unit. Upon examining the existing intelligence database on whether it contains comprehensive and relevant (complete) information to assess/analyze the particular assignment, unit analyst has the option of consulting various CF resources/disparate organizations by requesting supplementary information. Ultimately, the analyst provides feedback to the customers after collating all supplementary information. The feedback loops/mechanism for the information flow between the customers, Intelligence unit and the system resources (various disparate organizations) are displayed in Fig. 1.




 Intelligence Analyst Unit;

 Multiple CF resources/disparate organizations;



CF bases/customers.

Fig. 1 – Information Flow for the Intelligence Unit Cell

There are two possibilities occurring at the instance when unit analyst searches the intelligence database. For a particular tasking, the existing information might be incomplete with probability $p$, or complete with probability $1-p$. Based on his/her experience and perception on the completeness of existing information, unit analyst might request supplementary information from other CF resources. Thus there are two possible action outcomes characterized by probabilities $p_d$, $1- p_d$, denoting the wrong and right deduction on the completeness of existing information respectively, subscript $d$ denotes deduction made by unit analyst. Often times, unit analyst might also ill-understand and/or misinterpret the tasking from the client. As a result there is always the probability $p_c$ of receiving ambiguous supplementary information from other CF resources because of vague instructions from unit analyst that result in ill-understood and misinterpreted taskings by the CF resources. In such an event, supplementary information will again be solicited from disparate organizations but with more fine-tuned requests. There is also the $1- p_c$ probability that the requested supplementary information fulfills the demand and allows the analyst to assess/analyze customer tasking. The feedback process between the intelligence unit cell and system resources might take a few iterations before the requested information is fused, collated and forwarded to the customers.

## A DISCRETE TIME MARKOV CHAIN MODEL

Aside from the initial state where unit analyst receives tasking from customers, there are *4* other distinct states corresponding to the *2* possibilities on the perception of completeness of existing information in the intelligence database and the *2* different courses of action. The various states characterizing the conditions/status of information flow are summarized as follows:

$a_1$ = unit analyst receives tasking from customers; examines existing information in intelligence database for completeness (information relevant and comprehensive) so as to conduct analysis;

$a_2$ = unit analyst requests supplementary information from other CF resources where existing information in database is complete; however, analyst makes wrong deduction on the completeness of existing information;

$a_3$ = unit analyst requests supplementary information from other CF resources where existing information in database is incomplete; however, analyst makes right deduction on the completeness of existing information;

$a_4$ = existing information in database is complete; analyst makes right deduction on the completeness of existing information and provides assessment/analysis to customers;

$a_5$ = existing information in database is incomplete; analyst makes wrong deduction on the completeness of existing information and provides assessment/analysis to customers.

We construct the transition matrix by defining the following,

$p$ = probability that existing information in intelligence database is incomplete;

$p_d$ = probability that the analyst makes the wrong deduction on the completeness of existing information;

$p_c$ = probability of receiving ambiguous supplementary information from other CF resources,

which results in the following time homogeneous Discrete Time Markov Chain DTMC with transition matrix

$$
\mathbf{P} = \begin{array}{c|ccccc} & a_1 & a_2 & a_3 & a_4 & a_5 \\ \hline a_1 & 0 & (1-p)p_d & p(1-p_d) & (1-p)(1-p_d) & pp_d \\ a_2 & 1-p_c & p_c & 0 & 0 & 0 \\ a_3 & 1-p_c & 0 & p_c & 0 & 0 \\ a_4 & 0 & 0 & 0 & 1 & 0 \\ a_5 & 0 & 0 & 0 & 0 & 1 \end{array} \qquad (1)
$$

and transition diagram of the DTMC

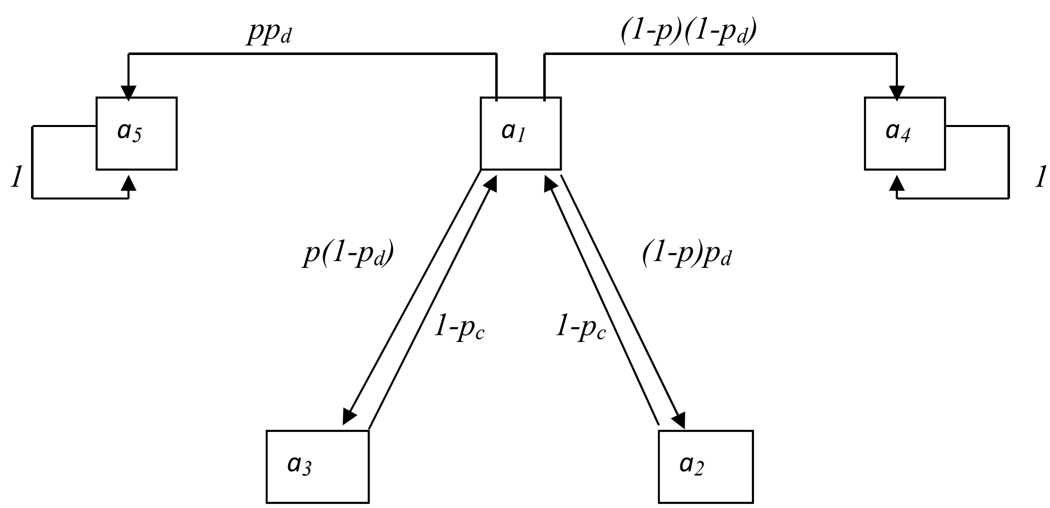



Fig. 2 – Transition Diagram of the DTMC for Intelligence Unit

In our formulation, we have assumed the transition time between allowable states is given by a known constant; the intent is to estimate the number of transitions until absorption at $a_4$ and $a_5$. The elapsed time (or the number of transitions) to absorption states does not distinguish between whether unit analyst has made a right or wrong analysis/assessment. The transition probability matrix ***P*** has *2* absorbing states $a_4, a_5$; and *3* transient states $a_1$, $a_2$, $a_3$. We rewrite the transition matrix in the following canonical form:

$$P = \begin{pmatrix} Q & R \\ 0 & I \end{pmatrix}$$

with transient matrix

$$Q = \begin{pmatrix} 0 & (1-p)p_d & p(1-p_d) \\ 1-p_c & p_c & 0 \\ 1-p_c & 0 & p_c \end{pmatrix}$$

absorbing matrix

$$R = \begin{pmatrix} (1-p)(1-p_d) & pp_d \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

and $I \equiv$ identity matrix. We calculate the time to absorption using well-established results in absorbing Markov Chain [10],

*Theorem* : In an absorbing Markov chain, the probability that the process will be absorbed is unity (i.e. $Q^n \to 0$ as $n \to \infty$). The matrix $I - Q$ has an inverse $N$ (fundamental matrix) and $N = (I - Q)^{-1} = I + Q + Q^2 + \ldots$. Let $t_i$ be the expected number of steps before the chain is absorbed, given that the chain starts in transient state, and let $t$ be the column vector whose $i^{th}$ entry is $t_i$. Then

$$t = Nc$$

where $c$ is a column vector all of whose entries are unity.

The entry $n_{ij}$ of the fundamental matrix $N$ gives the frequency that the process is in the transient state $q_j$ if it is started in the transient state $q_i$. The time required for humans in filtering, analyzing and redirecting information is then given by the frequency (transitions) from state $a_1$ to the absorbing states $a_4$ and $a_5$ multiplied by the time required per transition. Applying the above theorem and using symbolic computations, we can express the expectation value of the total time delay $T$ as a function of parameters $p$, $p_d$, $p_c$,

$$T = \frac{2p_d p - p - p_d - 1 + p_c}{p_c + 2p_d p_c p - p_d p_c - p_c p - 1 - 2p_d p + p_d + p} \qquad (2)$$

There is always a chance, represented by $p$, that the existing information in the intelligence database is incomplete for the assigned tasking. When unit analyst ill-understands and misinterprets the tasking, there exists the likelihood $p_c$ that he/she receives ambiguous supplementary information from other CF resources because of providing vague instructions. We are only interested in $p_c \geq p$, with $p$ being moderately small. The case where $p_c < p$ implies that unit analyst already provides fairly precise and succinct instructions to other CF resources on the requested supplementary information. Any resources devoted to improve the system or reduce the time latency will at best be marginal. With that in mind, we focus on the discussion of $p_c \geq p$. Consider the limiting case, $p_c \approx p$, we will highlight how parametric analysis on the closed form solution in equation (2) can provide valuable insights on the reduction of time latency of information in networked operations.

The magnitude of the slope of $T$ (the time latency function), with respect to $p_d$ (the probability unit analyst makes the wrong deduction on the completeness of the existing information in intelligence database) provides a measure of on changes in $T$ per change in $p_d$. Sharp increases in $\partial T/\partial p_d$ values should therefore be avoided, since it can dramatically lengthen the time delay of information. Similarly, steep $\partial T/\partial p_c$ values have the same effect on the latency function. We define

$$\Delta T = \frac{\partial T}{\partial p_d} - \frac{\partial T}{\partial p_c} \qquad (3)$$

and summarize the results deduced from $\Delta T$ as follows,

*Observations.* The breakeven point $(p_{d0}, p_{c0})$ is given by $\Delta T = 0$. For any other points $(p_{d1}, p_{c1})$ not equal to $(p_{d0}, p_{c0})$, $\Delta T$ *is either* $> 0$ *or* $< 0$,

(i) $\Delta T < 0$ at point $(p_{d1}, p_{c1})$, implying the increase in $T$ with respect to $p_c$ is faster than increase in $T$ with respect to $p_d$; in an era of limited resources, training should be provided to improve $p_c$;

(ii) $\Delta T > 0$ at point $(p_{d1}, p_{c1})$, training should be provided to improve $p_d$.

In brief, the magnitude of the differences between the slopes of time latency function with respect to $p_d$ and $p_c$ provides a measure for the effectiveness on various training alternatives.

*Proof*: by the definitions of $\partial T/\partial p_d$, $\partial T/\partial p_c$ .

EXAMPLE

The following fictitious data is a notional example to illustrate how collected information could be used to make training decisions. to improve the time delay of information in a CF intelligence unit under the effect of 'human in the loop'. Consider the following three sets of fictional data representing unit performance in the *1st* week of May, June and July *2013* respectively. Each data entry in the matrices represents the frequency of transitions between the states.

| | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $a_5$ |
|---|---|---|---|---|---|
| $a_1$ | 0 | 14 | 12 | 21 | 8 |
| $a_2$ | 8 | 5 | 0 | 0 | 0 |
| $a_3$ | 8 | 0 | 4 | 0 | 0 |
| $a_4$ | 0 | 0 | 0 | 21 | 0 |
| $a_5$ | 0 | 0 | 0 | 0 | 8 |

Data collected in *1st* week of May

| | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $a_5$ |
|---|---|---|---|---|---|
| $a_1$ | 0 | 14 | 12 | 22 | 7 |
| $a_2$ | 9 | 5 | 0 | 0 | 0 |
| $a_3$ | 8 | 0 | 5 | 0 | 0 |
| $a_4$ | 0 | 0 | 0 | 22 | 0 |
| $a_5$ | 0 | 0 | 0 | 0 | 7 |

Data collected in 1st week of June

| | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $a_5$ |
|---|---|---|---|---|---|
| $a_1$ | 0 | 13 | 11 | 20 | 7 |
| $a_2$ | 8 | 5 | 0 | 0 | 0 |
| $a_3$ | 8 | 0 | 4 | 0 | 0 |
| $a_4$ | 0 | 0 | 0 | 20 | 0 |
| $a_5$ | 0 | 0 | 0 | 0 | 7 |

Data collected in 1st week of July

In all the three sample periods, slightly more than half (*52%*) of the intelligence requests are assessed/analyzed based on existing information in intelligence database and no supplementary information had been requested from other CF disparate organizations. Over the one week period in May, the typical analyst processed 55 intelligence requests. Out of which, *21* requests or *38%* are based on unit analyst correctly deduced the completeness of information in the intelligence database where existing information in database is complete. This improved marginally in June (40%) and reverted back to *39%* according to the July sample. In reference to the DTMC transition matrix in equation (1), *39%* is the equivalence value of probability $(1-p)(1-p_d)$,

$$(1-p)(1-p_d) = 0.39$$

$$\text{or} \qquad p + p_d - pp_d = 0.61$$

A simple computation reveals the following relationships,

$$p = 0.3,\ p_d = 0.44;\ p = 0.4,\ p_d = 0.35;$$

$$p = 0.5,\ p_d = 0.22;\ p = 0.6,\ p_d = 0.025.$$

It is conceivable that low $p_d$ values (probability that the analyst makes the wrong deduction on the completeness of existing information) are difficult to attain (corresponding to moderately high $p$ values by the above expressions). Incoming tasking at the intelligence unit cell are often vague and can cause confusion among analysts. As a result, ill-understanding and misinterpretations on tasking happen. It is therefore reasonable to expect moderate $p_d$ values to occur (which corresponds to moderately small $p$ values, namely $p < 0.5$). This affirms our analysis focusing on moderately small $p$ values mentioned in an earlier paragraph.

Given the above experimental data, it would be pertinent to ask whether these three sets of transition probabilities reflect the same consistent behavior on the part of the intelligence analyst across the time period under consideration. If so, the data can be pooled to give a single transition count matrix and hence a single set of estimates. Essentially the issue here is whether or not the underlying Markov chain has a stationary transition probability matrix. We use the likelihood ratio test [11]: let

$$p_{ij}^{\ t} = P(X_{t+1} = j \mid X_t = i)$$

be the one-step transition probability from state $i$ to state $j$ at time $t$. Our null hypothesis is

$$H_0 : p_{ij}^{\ t} = p_{ij} \qquad \text{for } t = 1,..,3$$

To test $H_0$, denote $n_{ij}^{\ t}$ as the transition count from $i$ to $j$ in period $t$. For example, $t = 1, 2, 3$ represent respectively the chosen weeks in May, June, July and states $1, 2, 3, 4, 5$ correspond to $a_1$, $a_2$, $a_3$, $a_4$, $a_5$. Then $n_{12}^{\ 1} = 14$ means that $14$ pieces of information changed from state $a_1$ to $a_2$ in the chosen week $1$ in May. Under $H_0$, the likelihood ratio test statistics follows a $\chi^2$ distribution with $(T - 1)N(N - 1)$ degrees of freedom [10], $T$ is the total period, $N$ is the number of states,

$$\chi^2_{(T-1)(N)(N-1)} = 2\Sigma\Sigma\Sigma n_{ij}^{t} ln(\frac{\hat{p}_{ij}^{t}}{\hat{p}_{ij}})$$

$ln$ is the natural logarithmic function and $\hat{p}_{ij}^{t}$and $\hat{p}_{ij}$ are given by their maximum likelihood estimates (see [11] for derivation):

$$\hat{p}_{ij}^{t} = \frac{n_{ij}^{t}}{\sum_{j=1}^{5} n_{ij}^{t}} \qquad t = 1, 2, 3$$

$$\hat{p}_{ij} = \frac{\sum_{t=1}^{3} n_{ij}^{t}}{\sum_{t=1}^{3} \sum_{j=1}^{5} n_{ij}^{t}}$$

We wish to test the stationarity of the above three transition matrices, which tell us whether unit analysts shared similar experience and logic in perceiving the information across May to July.   The pooled transition counts is given by

| $n_{ij}$ | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $a_5$ | Total |
|---|---|---|---|---|---|---|
| $a_1$ | 0 | 41 | 35 | 63 | 22 | 161 |
| $a_2$ | 26 | 14 | 0 | 0 | 0 | 40 |
| $a_3$ | 24 | 0 | 13 | 0 | 0 | 37 |
| $a_4$ | 0 | 0 | 0 | 63 | 0 | 63 |
| $a_5$ | 0 | 0 | 0 | 0 | 22 | 22 |

and the estimate of the transition matrix for the pooled data is

| $\hat{p}_{ij}$ | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $a_5$ |
|---|---|---|---|---|---|
| $a_1$ | 0.00 | 0.26 | 0.22 | 0.39 | 0.14 |
| $a_2$ | 0.65 | 0.35 | 0.00 | 0.00 | 0.00 |
| $a_3$ | 0.65 | 0.00 | 0.35 | 0.00 | 0.00 |
| $a_4$ | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 |
| $a_5$ | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |

Under $H_0$, the $\chi^2$ statistic has $(3\text{-}1)*5*(5\text{-}1) = 40$ degrees of freedom.   Using the three sets of transition probabilities computed along with the above estimated transition probabilities for the pooled data, we obtain the computed $\chi^2 = 1.416 < \chi^2_{0.05}(40) = 55.76$.

Thus the null hypothesis of stationarity cannot be rejected. Combining the DTMC transition matrix in equation (1) and using the estimate of the transition matrix for the pooled data, we easily derive the following equalities,

$$(1-p)p_d = 0.26,\ p(1-p_d) = 0.22,\ p_c = 0.35,\ (1-p)(1-p_d) = 0.39,\ pp_d = 0.14$$

After simple algebraic manipulations, we obtain

$$p_c = p = 0.35,\ 0.389 \leq p_c \leq 0.4$$

At $(p_c, p_d) = (0.35,\ 0.4)$, $\Delta T = \partial T/\partial p_d - \partial T/\partial p_c = -1.195 < 0$, and at

$(p_c, p_d) = (0.35,\ 0.389)$, $\Delta T = \partial T/\partial p_d - \partial T/\partial p_c = -1.375 < 0$,

according to our observation, training should therefore be provided to intelligence analyst to improve $p_c$.

## CONCLUSION

Time has always been of crucial importance in military networked operations, and consequently of Command and Control. As Lawson [7] relates, "….in a typical discussion of Command and Control, it is taken as axiomatic that the information presented to the commander must be timely as well as accurate, complete etc… Little or nothing is said about how timely is timely enough; nor is any yardstick given by which to measure 'timeliness'…".

Instead of endeavoring to quantify timeliness, in this paper we suggest means to reduce the time latency of information through training. This is by no means establishing a metric for the timeliness measurement; the aim is to improve the degree to which mission performance depends on timely and perhaps perishable information. This is accomplished through mathematical formulation via a Discrete Time Markov Chain Model. Closed form solution on the time latency of information under the influence of 'human in the loop' is obtained using symbolic computations. We then summarize our findings by observing that the magnitude of the differences between the slopes of time latency function with respect to the key governing parameters provides a measure for the effectiveness on various training alternatives. Data on the intelligence unit is collected and employed to highlight our methodology.

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