Forecasting of Radio Frequency Identification Entropy Viscosity Parking and Forwarding Algorithm Flow Risks and Costs: Integrated Supply Chain Health Manufacturing System (ISCHMS) Approach

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***Abstract*—Our research hypothesis is that we could improve traditional supply chain management (SCM) health by designing a new integrated manufacturing enterprise system based on parking and forwarding algorithms, radio frequency identification (RFID) feedback and a Markov decision process. The goal of our research was to optimize a cost function that depends on RFID system viscosity. The viscosity of the RFID can be defined as the flow of data through the RFID network. This process can be measured by the entropy of the parking and forwarding of the signal, leading to a sustainable supply chain system. The dynamics of this system are governed by differential equations. Using this entropy model, we verified the integrated supply chain health manufacturing system risk failure reduction via simulation. Our method employs a fuzzy Kalman filter, improves the system, reduces backorders and demonstrates that RFID viscosity is an effective means to this end. A Markov blanket entropy approach demonstrated that it can capture and provide a theory of RFID viscosity parking and forwarding algorithms as a networking solution to lowering SCM costs, reducing waste, and improving sustainability.**

***Index Terms*—Inventory manufacturing, Markov process, radio frequency identification (RFID), supply chain management.**

I. Introduction

MASH networking is a wireless networking protocol in which Mash points form a network of communications among themselves, collecting and routing data to various NIPRNet (Non-Classified Internet Protocol Router Network) systems to enhance and improve logistics business processes. A Mash network by definition is fault tolerant, with built-in connection redundancies. It features ad hoc, self-forming/self-healing, fully encrypted data agnostic technology that is multitasking (AMATS). AMATS is the Army Mobility Asset Tracking System (U.S. Army). AMATS has been installed at many military bases to provide end-to-end asset visibility. The current process is expensive, inefficient, and ineffective. It provides limited visibility and significant challenges in terms of oversight, with increased cost. Mash increases asset visibility, improves operational efficiency, and reduces operational costs. Long-term plans include yard management and transportation throughout the Army. It has successfully met its objective to provide near real-time visibility and can identify Army business processes that can be optimized by automated collection and reporting of data from Mash. This paper investigates a Radio Frequency Identification Viscosity Parking and Forwarding Algorithm with a fuzzy Kalman filter. It also employs an entropy Markov process model for collaborative forecasting of radio frequency identification (RFID) parking and forwarding viscosity flows to achieve optimal network control, reduce backorder failure risk, and lower cost in an ISCHMS. Each node is conditionally independent of all others given its Markov blanket: parents + children + children's parents. This manufacturing system was used to determine the supply chain state of wireless sensor networks that can rapidly deploy an optimal multihop network.

Examples of sensors that predict backorders include customer inventory sensors, customer buying plan sensors, customer quantity requested driver sensors, customer plans and indicators, bills of materials, raw material status sensors, direct and indirect competing quantity requested sensors, voice messaging and audio sensors, manufacturing and repair schedules and report sensors and product lifecycle sensors. Many of these sensors are from data buried in customer and supplier databases and reports to which access is needed to be useful. That is why members of a common supply chain share information, subject to trading partner agreements that protect its proprietary nature while being open to those who can benefit from it in their own decision making. Effective and efficient ISCHMS is an important component and it has an impact on the supply chain management (SCM) data bus. The goal of the current effort was to decrease entropy and reduce costs, while increasing RFID viscosity algorithms for parking and forwarding information flows.

As was stated earlier, customer inventory sensors, customer buying plan sensors, customer quantity requested driver

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sensors, customer plans and indicators, bills of materials, raw material status sensors, direct and indirect competing quantity requested sensors, voice messaging and audio sensors, manufacturing and repair schedules and report sensors and product lifecycle. In our model, the BOM and raw material subsystems were combined to determine the supply chain material availability. Supply chain financials and information made up the other subsystems. Once the Integrated Supply Chain Health Manufacturing System (ISCHMS) was constructed, we gathered real-world data for predicting backorders. After learning this structure, we measured the entropy components and used stochastic simulation based on Markov blankets to learn the posterior distribution of backorder costs. We used simulation approaches to learn the posterior distribution of variables in a Bayesian like network. We describe our real-world supply chain data set and provide the results of our experiments as well as a summary and directions for decreasing costs. We lay the framework for future work in reducing entropy, increasing effectiveness and improving RFID parking and forwarding viscosity algorithms.

A. RFID Literature Review and SCM

RFID is ubiquitous and it is found in many of our modern life processes [1]–[3]. This is especially true in SCM as there is much synergy, optimization, fault tolerance, efficiencies and synchronization needed between the RFID and SCM components of a computer network [4]–[8]. These synergies also include security issues and filtering [9], [10]. Network planning and reducing uncertainty is also very important as well as tag parameters [11]–[14]. Protocols guides for the RFID model and functionality are also essential [15], [16].

SCM has been revolutionized by the RFID and computer network applications strategy [17]. For example, Lu *et al.* [18] designed a SCM key process model. Govindan and Soleimani [19] (2017) conducted a comprehensive review of the publications in the field of reverse logistics and closed-loop supply chains. In many of these selected papers RFID played a significant role in SCM sustainability [20]. Kumar and Rahman [21] (2014) demonstrated an application of the RFID-enabled process reengineering in sustainable healthcare system design. Cui *et al.* [22] (2017) explored the different effectiveness of RFID in decreasing the inventory inaccuracies in a supply chain containing one retailer and two suppliers. Jaggi *et al.* [23] (2014) identified two complementary strategies that are required to address RFID reliability. These applications are improving the reliability of RFID technology and/or designing packaging related infrastructure that enables RFID. The paper focused on designing RFID Ready facilities (RRF), and an RFID-enabling packaging infrastructure that helps avoid unnecessary transportation.

Piramuthua and Doss [24] (2017) critically evaluated the use of various relevant ambient conditions for simultaneous authentication of multiple tags as well as the verification of their simultaneous physical proximity to the reader. Chai [25] (2017) improved RFID tracking performance in industrial sites by developing a RFID tracking method that integrates Multidimensional Support Vector Regression (MSVR) and a Kalman filter. Zhong [26] (2015) demonstrated that RFID technology was used in manufacturing industries to create an RFID-enabled ubiquitous environment in which ultimate real-time advanced production planning and scheduling was achieved with the goal of collective intelligence. Song *et al.* [27] (2017) investigated the SCM inventory policy problem for a dual source. It can be seen from the foregoing literature that there are many benefits of RFID technology for reducing inventory shrinkage and optimization of SCM processes. (Zhou and Piramuthu [28] 2013; Ngai *et al.* [29] 2014; Fan *et al.* [30] [31] 2014, 2015; Anderson *et al.* [32] 2017).

II. A Review of Multisensor Data Fusion Applications, Fuzzy Logic and Kalman Filtering

Mangla *et al.* [33] (2017) proposed a fuzzy Analytical Hierarchy Process to determine the priority of concerns of the identified barriers related to implementing SCP trends in supply chain under fuzzy surroundings. Their research findings indicate that the Organizational barriers dimension obtains the highest priority and serves as a key hurdle in achieving SCP trends in supply chains. Kannan *et al.* [34] (2015) proposed a multi-criteria decision-making (MCDM) approach called Fuzzy Axiomatic Design (FAD) to select the best green supplier for a Singapore-based plastic manufacturing company. Lin [35] (2013) utilized the fuzzy set theory and decision making trial and evaluation laboratory method to form a structural model to find out the cause and effect relationships among eight criteria of three main SCM factors, namely practices, performances, and external pressures. Ortas *et al.* [36] (2013) employed a Kalman filter aimed to provide relevant information about the outcomes of integrating environmental, social and governance issues for cleaner production into investment strategies in the Asia Pacific region for managers, practitioners, academics, institutions and investors.

Aiello *et al.* [37] (2017) proposed a methodological approach to the development of a DSS in the specific context of Integrated Pest Management (IPM) applied to intensive (greenhouse) production. Using an experimental validation based on real data, the DSS involves a rule-based decision approach based on referenced mathematical models applied to the information gathered by a sensor network. Maleki *et al.* [38] (2014) addressed the joint problem of configuring a hybrid wired-cum-wireless sensor network, position-constrained cluster head location, sensor nodes allocation, and position-constrained access point placement. Bonvoisin *et al.* [39] (2012) provide a method to analyze Wireless Sensor Networks in an environmental perspective. They clarify two important issues: the definition of the system lifecycle and the synergic behavior of its elements. From an RFID perspective, fuzzy multisensor data fusion using a Kalman filter has received very little attention in the literature. Recently, however, Wang *et al.* [40] (2016) employed a fuzzy multiple objective linear programming (FMOLP) model to integrate designed systems for making decision associated with environmental regulations and cost-effectiveness of carbon emissions in manufacturing firms.

Markov decision processes that utilize state spaces have long been common in the literature and may be applied to compute an optimal policy and average cost optimality (Aviv and Federgruen [41] 1999; Fleming [42] 1966; Soner [43] 1993). Kalman filtering is a estimating technique that serves as a model based on a linear space state. To improve RFID parking and forwarding viscosity, we first present a partially observable Markov decision process to estimate future quantity requested. Let $\{X_t\}$ be a finite, state-of-the-system, n-dimensional vector process. This state vector can evolve accordingly:

Dynamics of state space:

$$X_t = FX_{t-1} + V_t, \tag{1}$$

with an n × n matrix and F being not dependent on time. The white noise process is represented by the vectors $\{V_t \in \mathbf{R}^n : t \geq 1\}$. Each random vector V_t has a mean $\mathbf{0}_{nx1}$ and covariance matrix $\sum_V$. The state vector X_t is partially or fully observed by the decision maker. Only the vector is observed during time time t, and it is determined that H is an m × n matrix and the observation equation is

$$\Psi_t = H_t \in \mathbf{R}^m. \tag{2}$$

If Ψ_t is the decision maker's collected information during time t and D_t represents the realized quantity requested during time t, then the quantity requested can be considered to be a linear function and deterministic with the quantity requested equation as follows:

$$D_t = \mu + R\Psi_t, \tag{3}$$

where R has known parameters as a 1 × m vector and the known scalar is μ. We utilize the minimum MSE X_t, previous data $\{\Psi_{t-1}, \Psi_{t-2}, \ldots \Psi_1\}$, and calculate $\hat{X}_t = E[X_t|\Psi_{t-1}, \Psi_{t-2}, \ldots \Psi_1]$. In addition, let $\grave{U}_t^X = E[(X_t - \hat{X}_t)(X_t - \hat{X}_t)^!]$ be the error covariance.

The fuzzy Kalman filter approach (FKFA) is adapted to compute the values of $\hat{X}_t$ and $\grave{U}_t^X$. With an initial state vector estimate of $\hat{X}_1$ and a beginning error covariance matrix of $\grave{U}_1^X$, then every initial time t has an estimate $\hat{X}_t$ derived from the following:

$$\hat{X}_t = F\hat{X}_{t-1} + FK_{t-1}\left(\Psi_{t-1-}H\hat{X}_{t-1}\right). \tag{4}$$

Furthermore, the associated error covariance matrix is:

$$\grave{U}_t^x = F\grave{U}_{t-1}^x F^! - FK_{t-1}H\grave{U}_{t-1}^x F^! + \sum V, \tag{5}$$

The raw material availability difference and customer wait time difference fuzzy membership functions of our study are shown in Figure 1.

The remainder of the manuscript follows. Section III provides a brief overview of the Markov process simulation. Section IV describes the Model Development Model Testing, Simulation and Verification for the SCM and MIST (Military Information System Technology) RFID. Section V contains the Real Options Theory, Colored Petri Nets and Fuzzy Logic Markov Process ISCHMS Optimal Price Control results for the model. Section VII gives the discussion and recommendations. Section VIII provides the conclusions and future issues.

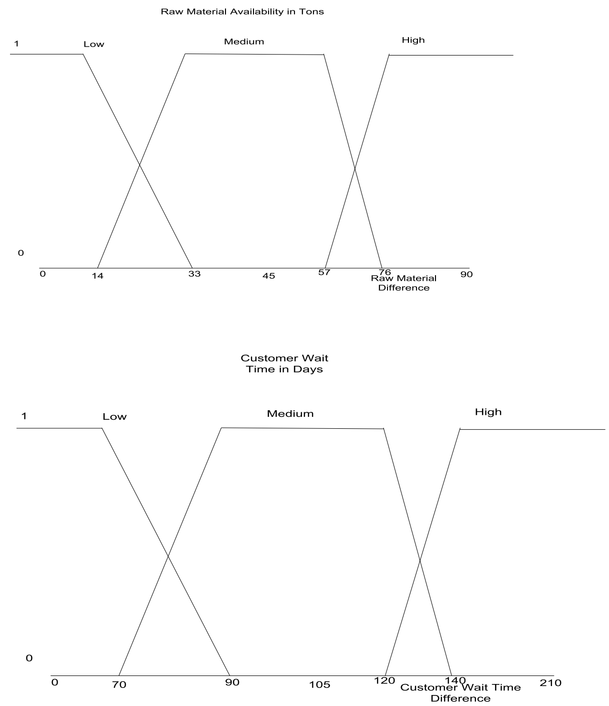

Fig. 1. Raw material availability difference and customer wait time difference fuzzy membership.

III. Overview of Simulation With Markov Processes

Markov Decision Process was used to model the system state evolutions. We are applying Markov processes to RFID parking and forwarding viscosity algorithms for goods in stock control. First, we must consider SC process decision making for n raw material. Let $x_i(s)$ and $u_i(s)$ represent the goods in stock category level and rate of manufacture, respectively, for commodity $i = 1, \ldots n$ at period s. Assume that quantity requested is a fixed constant d_i that this is known to the decision maker. Let

$$x(s) = x_1(s), \ldots x_n(s), u(s) = u_1(s), \ldots u_n(s), d = (d_1 \ldots d_n). \tag{6}$$

These are the goods in stock and control vectors at time s and the quantity requested vector, respectively. The delta of the goods in stock $x(s) \in \boldsymbol{IR}^n$ is

$$\frac{d}{d_s} - x(s) = u(s) - d. \tag{7}$$

For a given finite period interval $t \leq s \leq t_1$ and an initial goods in stock $x(t) = x$ one would like to minimize the manufacturing rate $u(s)$

$$\int_t^{t1} h(x(s))ds + \in \psi(x(t_1)), \tag{8}$$

where t_1 is the end time, h the running price, and Ψ the end price. A typical example of h is

$$\mathrm{h(x)} = \sum_{\mathrm{I}=1}^{\mathrm{n}} \left[\acute{\mathrm{a}}_i (x_i)^+ + \tilde{\mathrm{a}}_i (x_i)^- \right], \tag{9}$$

where $\acute{a}_i$ and $\tilde{a}_i$ are positive constants interpreted as a unit holding price and a unit shortage price, respectively, and $a^+ = \max\{a, 0\}$, $a^- = \max(-a, 0\}$. Therefore, this manufacturing decision making problem is to minimize Eq. (11) subject to Eq. (10), with the initial condition $x(t) = x$ and the control constraint $u(s) \in \mathrm{U}$ where

$$\mathrm{U} = \left\{ \mathrm{v} \in \boldsymbol{IR}^{\mathrm{n}} : \mathrm{v}_i = 1 \ldots \mathrm{n}, \sum_{\mathrm{I}=1}^{\mathrm{n}} \mathrm{c_i v_i} \le 1 \right\}. \tag{10}$$

Estimateing RFID parking and forwarding viscosity solutions may be discontinuous. Therefore, let W be a bounded real value function on $\bar{Q}$ and define the upper and lower not fully continuous container of W as follows:

The upper not fully continuous container of W is

$$\begin{aligned} (\mathrm{W})^*(\mathrm{t, x}) &= \text{lim sup } \mathrm{W(s, y)}, \forall (\mathrm{t, x}) \in \bar{Q} \\ &(\mathrm{s, y}) \to (\mathrm{t, x}) \\ &(\mathrm{s, y}) \to \in \bar{Q}. \end{aligned} \tag{11}$$

The lower not fully continuous container of W is

$$\begin{aligned} (\mathrm{W})_*(\mathrm{t, x}) &= \text{lim inf } \mathrm{W(s, y)}, \forall (\mathrm{t, x}) \in \bar{Q} \\ &(\mathrm{s, y}) \to (\mathrm{t, x}) \\ &(\mathrm{s, y}) \to \in \bar{Q}. \end{aligned} \tag{12}$$

Note that (W)* is the smallest upper not fully continuous function that is greater than or equal to W.

In determining RFID viscosity, some identifiable environmental factors may be unpredictable (e.g., obsolescence magnitude and timing, products whose quantity requested can be explained statistically, and uncertain new product quantity requested increase and timing). In these cases, nonstationary models with fixed patterns $\{G_t\}$ are inadequate. During a specific time frame t, if we let a quantity requested state (I_t) suppose that it can take one of N values, $\{1, 2, \ldots N\}$. According to a Markov chain, I_t evolves in the probability matrix $P = \{p_{xy}\}$. Given that $I_t = I$ during time period t, one can denote the conditional density function of the quantity requested as Ø(d|i). The quantity requested evolution and the estimatess are given by the transition matrix P and the conditional distributions Ø when the state of the quantity requested process $\{I_t\}$ is observable. Because it is necessary to keep some history information $\{I_1, \ldots I_t\}$, let $\eth_t$ be a vector of probabilities $(\eth_{1t}, \ldots . \eth_{Nt})$ that represents the current state of quantity requested knowledge. Therefore, an essential component of the evolution estimate process is that the quantity requested and the vector can be updated as follows:

$$\eth_{\mathrm{i,t+1}|}\left(\eth_{\mathrm{i,t}}, \mathrm{d_t}\right) = \frac{\sum_{\mathrm{j}=1}^{\mathrm{N}} \eth_{\mathrm{jt}} \text{Ø}(\mathrm{d_t j}) \mathrm{p_{ji}}}{\sum_{\mathrm{j}=1}^{\mathrm{N}} \eth_{\mathrm{jt}} \text{Ø}(\mathrm{d_t j})}. \tag{13}$$

In this multi-item system model, assume that unsatisfied quantity requested is backlogged and that manufacturing volumes and manufacturing prices are proportional in both phases. Also assume a periodicity K for all price parameters, quantity requested distributions, and capacity limits. Whether a batch of voids and what size are determined at the beginning of each time $n = 1, 2, \ldots$ by the decision maker. The batch is allocated to J end products when it is completed at the initialization of time $n + L$. After a possible second production step, the voids allocated to product j $(j = 1, \ldots J)$ become available as units of the end product j at the initialization of each time $n + L + l_j$. Quantity requesteds in the k-th time of any cycle of K times are identically distributed as the vector $d^k = (d_1^k, \ldots d_{j,}^k)$. Let x_j = the goods in stock position of item j at the initialization of a time and before allocation of this time's manufacturing batch of voids, y_j = the goods in stock position of item j at the initialization of a time and after allocation of this time's manufacturing batch of voids, w = the size of the batch of voids ordered at the initialization of a time, w^r = the size of the batch of voids ordered r times before the initialization of a given time $(r = 1, \ldots L)$, b^k = the capacity in times of category k $(k = 0, \ldots K - 1)$, γ^k = the first-step manufacturing price rate for voids in times of type k $(k = 0, \ldots K - 1)$, and c_j^k = the variable second-step manufacturing price rate for item j in times of category k $(j = 1, \ldots J;\ k = 0, \ldots K - 1)$.

Assume that future prices are discounted by a factor $\alpha \le 1$ and the expected value of all other price components for item j $(j = 1, \ldots J)$ charged to a time of category k $(k = 0, \ldots K - 1)$ that can be expressed as a function $G_j^k y_j$. Assume that the backlog carrying price incurred for an goods in stock backlog of $x_j^+ (x_j^-)$ units at the end of a time of category k is given by $h_j^k (x_j^+)(p_j^k (x -_j))$. Therefore, each discounted holding and backlog price incurred one lead time later is $G_j^k y_j = \sim G_j^k (y_{j;} l_j)$, where

$$\sim \mathrm{G_j^k}\left(\mathrm{y_{j;}l}\right) = \alpha^{\mathrm{l}} E \left\{ \mathrm{h_j^{k\oplus l}} \left(\left[\mathrm{y_j} - \mathrm{d_j^k} - \mathrm{d_j^{k\oplus l}} \ldots - \mathrm{d_j^{k\oplus l}} \right]^+ \right) + \mathrm{p_j^{k\oplus l}} \left(\left[\mathrm{d_j^k} + \mathrm{d_j^{k\oplus l}} \ldots + \mathrm{d_j^{k\oplus l}} - \mathrm{y_j} \right\} \right. \right. \tag{14}$$

and where $a \oplus b_{=.} (a + b) \bmod K$.

This study proposes an increase in RFID viscosity information flows by the Mash system. Assume that two nodes X and Y take discrete values in finite sets x and y. The mutual information metric, I(X,Y), for these two nodes is given as follows:

$$I(X, Y) =_{\sum \mathrm{x,y}} P(x, y) \log^{\underline{P(x,y)}} p(x) p(y). \tag{15}$$

If there is another node Z that takes discrete values in finite set z, then the conditional mutual information metric for X and Y conditioned on Z is defined as follows.

$$I(X, Y|Z) =_{\sum x,y,z} P(x, y, z) \log^{\underline{\mathrm{P(x,y|z)}}} p(x|z) p(y|z). \tag{16}$$

The independence of nodes X and Y is determined using an arbitrary threshold value. If I(X,Y) <, then nodes X and Y are called marginally independent of each other. Furthermore, if I(X,Y|Z) <, then nodes X and Y are called conditionally independent of node Z.

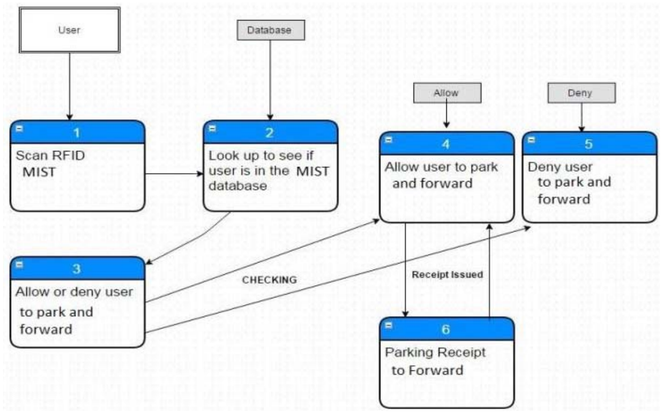

Fig. 2. High-level system prototype schematic.

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IV. Model Development Model Testing, Simulation and Verification

In model-based fault detection and isolation (FDI), we improved inefficiencies in the supply chain model via Bayesian posterior probobilities. Using the four composite sensors, we designed an ISCHMS with the associated databases and applied separately made up combinations of the raw materials and financial flows, the financial and information flows, and the raw materials and information flows. The ISCHMS is combined with the scheme for the RFID data fusion method as illustrated in Figure 2.

Our approach becomes more important as the need increases to decrease failure risks that can be within acceptable solution ranges. For example, the posterior conditions of buyers that specify the maximum supply chain backorder time at 90 days may consider 110 days as acceptable customer wait times. The raw material adjustments flow diagram is illustrated in Figure 3. The Integrated supply chain health manufacturing system (ISCHMS) is demonstrated in Figure 4.

MIST (monitoring, identification, security, and tracking) was originally developed to support the U.S. Department of Defense (DoD) and expands the transparencies within this distributed system. Mash networking was developed that is compatible with the existing DoD RF/ITV system. MIST is better than RFID because it is more efficient. These efficiencies are measured by the following parameters. MIST has a reduced infrastructure requirement; has a lower capital investment; provides two-way communication; has a longer batte\ry life; is a dynamic, self-organizing, and self-healing network; and supports mobile ad hoc networking in which every tag is an end node and router. Furthermore, it is built on a true global standard (802.15.4), has no unsolicited RF transmissions in which a high density of tags is not a problem (4 million addresses per network), and has the ability to operate in harsh RF environments (ports) with 16 different

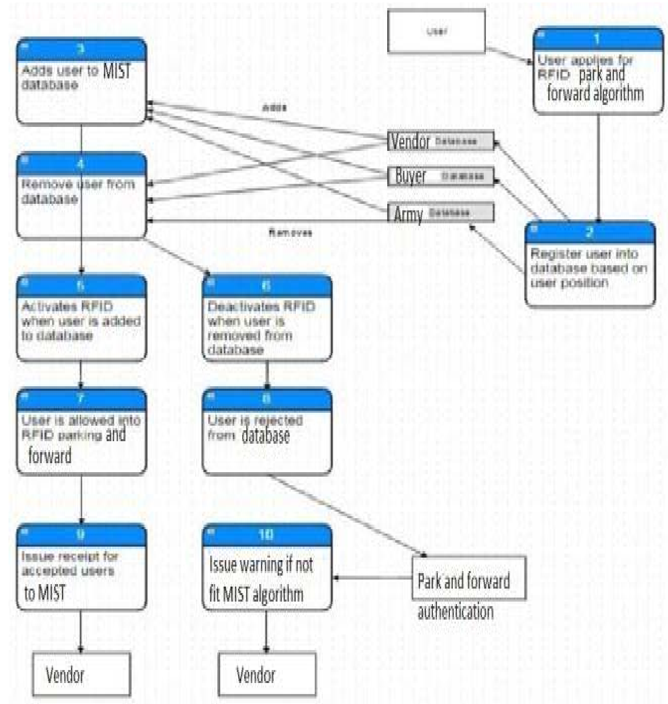

Fig. 3. Raw material adjustments flow diagram.

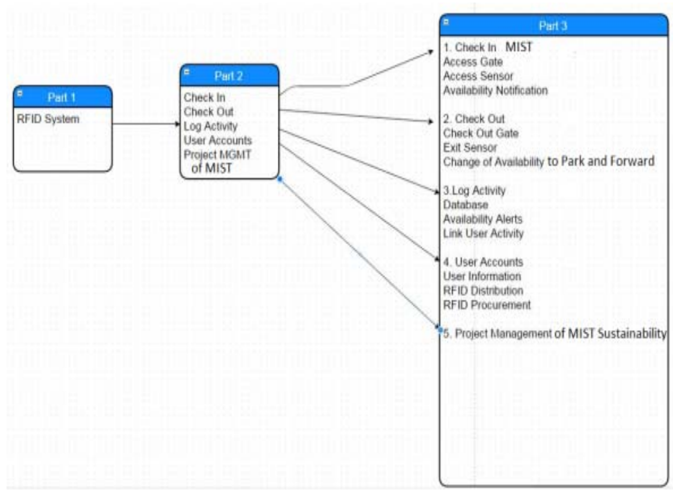

Fig. 4. Integrated supply chain health manufacturing system (ISCHMS).

channels. In addition, the MIST Evaluation Kit provides full control through MIST Network Management Protocol, the ability to send arbitrary messages using a variety of algorithms and routing schemas, such as park and forward, the ability to decrease entropy and measure the power consumption of each node, Mash visualization, and the ability to connect a host to any Mash modem in which each modem (sink) can form the network or be just a Mash router. These capabilities can be dynamically switched on or off on each device at any time independently and include a MIST file transfer and OTA upgrade. A ping/trace route with route reporting based, periodic and on change is also included. These capabilities can also measure data communication reliability and network stability; the ability to form logically separated networks;

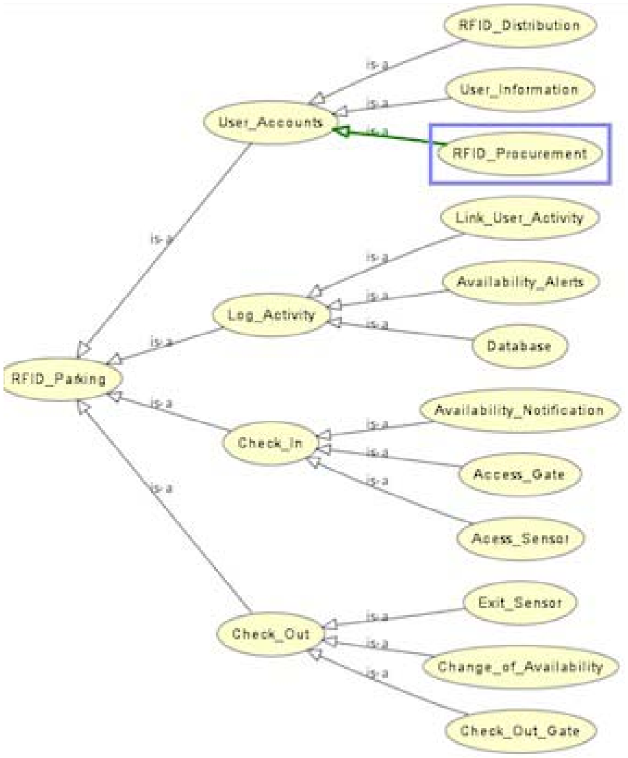

Fig. 5. Ontology structure for MIST real options.

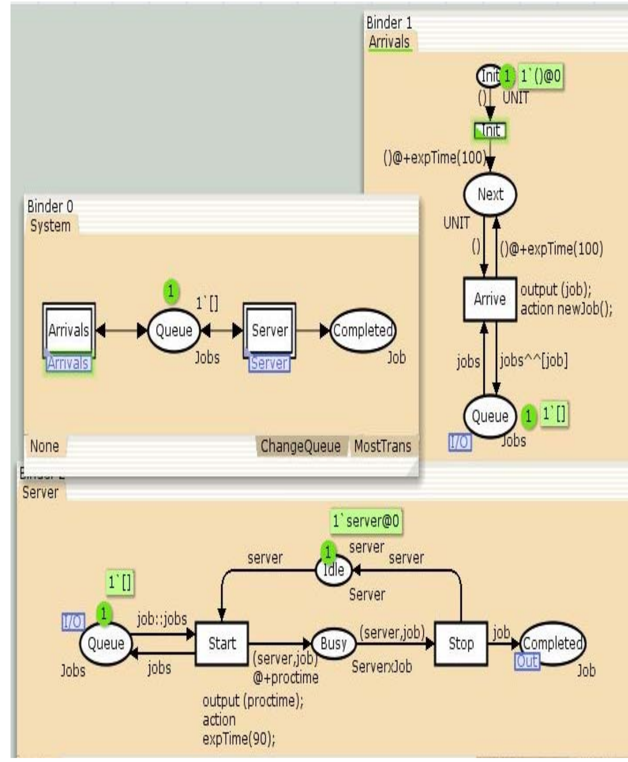

Fig. 6. MIST Petri net transition diagram for inventory backorder request query system.

the ability to control critical security parameters; the ability to control various networking parameters, such as latency, throughput, and priority; the ability to maintain highly accurate Greenwich Mean Time across the network using MIST NTP; the ability to bind devices inside an ad hoc network; and the ability to set RFID-style bidirectional broadcasting.

The device has integrated sensors, can use wired sensors, and supports an M2M interface. Dry Container solution is composed of a Warrior device that has integrated door-state sensors and is easily mounted on the middle of the door header beam. The device includes other sensors to monitor intrusion from other locations besides the doors and cargo-specific sensors.

V. Real Options Theory, Colored Petri Nets and ISCHMS Optimal Price Control

The fuzzy ontology for MIST real options is shown in Figure 5.

Option contracts and portfolio management have been applied to supplier contracts (Anderson *et al*. 2017 [32]; Bansal and Nagarajan [44], 2017). Fuzzy linguistic ontologies can be used for real option valuation. Further, simulation methods such as Colored Petri Nets may be used to enhance the visualization of the Mash networking application. The MIST query system for the inventory backorder process is shown in Figure 6.

Real options theory allows for the contingencies of future investments in the MIST project. Simulation methods such as Colored Petri Nets may be used to enhance visualization of the Mash application. More than $10 million in proposed savings can be realized by implementing the AMATS approach through savings in labor costs alone. Below is a decision tree and Markov analysis for our proposed algorithm that will aid in our decision making. It makes suggestions for abandoning, containing, or expanding the Mash application under real option conditions ranging from pessimistic to most likely to optimistic.

When the proposed RFID changes are implemented, the general logistics Army business case will help the Army to save money and research analytical methods that can be used to integrate a wireless network Mash across the enterprise. The Mash system will provide flexibility. It has already been partially rolled out, by implementing rolling stock and demonstrating efficiency under one application. The system has a projected $10 million savings as well as other compelling benefits if it is used to its fullest. This savings revolves around implementing AMATS at $4.6 million, which will cost $160 per unit compared to $98 per unit for RFIF. However, the labor cost of installing AMATS is only $5.7 million compared to $20.3 million with no AMATS. The hardware will remain the same at approximately $240,000. This application is able to cover the yard with fewer infrastructures by using ad hoc, mobile, self-healing operating maintenance. The system is not nodal, is streamlined, and is capable of making acquisitions with fewer infrastructures through product package transmission that is risk averse and provides a snapshot of condition-based maintenance. The application is scalar and can easily add other major areas.

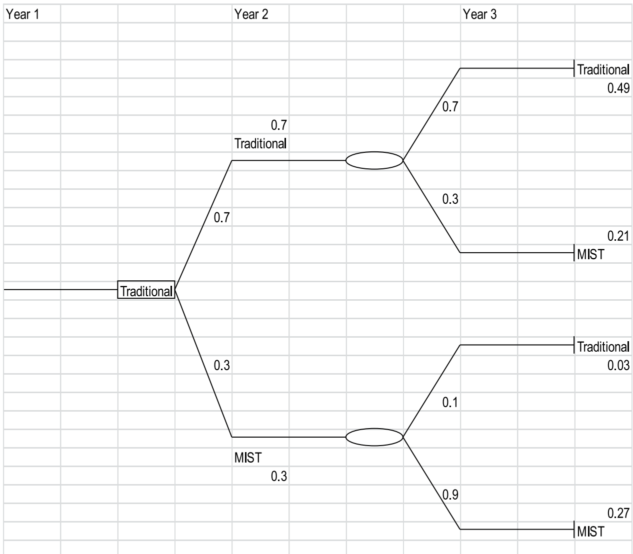

Fig. 7. RFID Decision Tree.

TABLE I
VENDOR MOVING FROM TRADITIONAL RFID TO MIST RFID MATRIX

	Traditional	MIST
Traditional	.70	.30
MIST	.10	.90

A. *Decision Trees and Markov Analysis*

We can use both a decision tree and Markov analysis to determine the probability that a vendor would use the MIST RFID in year 3, given that the vendor used it this first year. This analysis was initially conceptualized using a decision tree, as shown in Figure 7. To determine the probability of a vendor using the traditional RFID in year 3, given that the vendor initially used the traditional RFID in year 1, we use the decision tree as seen in Figure 7. We find that the probability associated with the vendor using the traditional RFID in year 3 is $.49 + .21 = .70$. In a similar manner, we find that the probability is $.03 + .27 = .30$, of a vendor using MIST RFID in year 3. While the decision tree was a good start, we used the Markov Process to predict MIST RFID usage by year 4.

Markov analysis was employed to determine the probability of adoption of the new MIST system on a yearly basis. The Army surveyed a number of its suppliers to determine the viability of the MIST system over the traditional RFID that was currently in place. The Army felt that the suppliers were willing to change due to the quicker transfer times and longer range of MIST, despite the down side of switching costs. The Army found that if a vendor used the traditional RFID in a given year then there was only a .70 probability that the vendor would use it again the next year and a .30 probability that the vendor would use MIST. However, if a vendor used MIST in a given year, there was a .90 probability that the vendor would use MIST in the next year and a .10 probability that the vendor would use the traditional RFID, due to the advanced technological capabilities of MIST. The original first year can be illustrated in tabular form as an array or transition (T) matrix as shown in Table I.

Therefore, there is a .70 probability that a vendor who used traditional RFID in year one will utilize it in year two. We can define the probability of a vendor using traditional RFID in time *i*, given that the vendor initially utilized traditional RFID.

Therefore for $\mathrm{T_p}(i)$

Probability of using traditional RFID $=$ T

Initial starting state of traditional RFID $=_{\mathrm{p}}$

Future time $i =$ (i)

We can also define the probability of a vendor using MIST RFID in time *i*, given that the vendor initially utilized traditional RFID.

Therefore for $\mathrm{M_p}(i)$

Probability of using MIST RFID $=$ M

Initial starting state of traditional RFID $=_{\mathrm{p}}$

Future time $i =$ (i)

It follows that the probability of a vendor utilizing MIST RFID in year 2, given that the vendor initially used Traditional RFID, is

$$\mathrm{T_p}(2)$$

The probabilities of a vendor utilizing traditional and MIST in a future time *i* given that the vendor initially utilized MIST, are defined as

$$\mathrm{T_n}(i) \text{ and } \mathrm{M_n}(i)$$

This transition matrix defines the starting conditions of our RFID system, given that a vendor initially utilizes traditional RFID, as was illustrated in the decision tree above. The state probabilities for several subsequent years are as follows:

year 2: [Tp(2) Mp(2) = [.52 .48]

year 3: [Tp(3) Mp(3) = [.41 .59]

year 4: [Tp(4) Mp(4) = [.35 .65]

The state probabilities that result after some future year, *i*, are: $[\mathrm{Tp}(i)\mathrm{Mp}(i)] = [.35.65]$. It can be seen that after four years, MIST will have captured a majority of the RFID market share. These advances will become smaller unless MIST develops a newer, more advanced technology or if it can prove to their vendors the continued superior utility of their product in terms of ensuring further distance sensing, better antennae function, superior MIST reader manufacturer and better overall MIST tag type and orientation.

B. *Fuzzy Logic Application of Markov Steady-State Probabilities*

The Markov Process can help to predict the percentage of vendors who will utilize an RFID during any given year in the future. For example, if there are 500,000 vendors in the Army who utilize RFID technology, then in the future the expected numbers of vendors who will use the MIST and Traditional RFIDs on a yearly basis are as follows:

$$\begin{aligned}\text{MIST} : \mathrm{M_p}\ (500,000) &= .65(500,000)325,000 \text{ vendors}\\ \text{Traditional} : \mathrm{T_p}\ (500,000) &= .35(500,000)\\ &= 175,000 \text{ vendors}\end{aligned}$$

The real option fuzzy logic scenarios above can also be applied to the Makov Process. For example.

TABLE II
CHI-SQUARE TEST

Chi-Square Tests

	Value	df	Sig
Pearson Chi-Square	238.483[a]	15	.000
Likelihood Ratio	218.090	15	.000
Linear-by-Linear Association	39.534	1	.000
N of Valid Cases	302		

a. 11 cells (45.8%) have expected count less than 5. The minimum expected count is .10.

If revenues are optimistic at $2,450 M then (.65) MIST should expect $1592 Million income. If revenues are most likely at $2,400 M then (.65) MIST should expect $1560 Million income. If revenues are pessimistic at $2,350 M then (.65) MIST should expect $1527.5 Million income.

VI. ENTROPY, CLASSIFICATION AND STATISTICAL COMPARISON OF MIST AND TRADITIONAL RFID

The study of dynamical systems, such as a supply chain, involves a time series as a key task. An efficient supply chain is efficient, has little chaos and it is highly correlated with useful enthalpy or energy, little entropy and maximum work. The SCM time series strives to be very ordered. One of the most natural measures of disorder, and thus the absence of correlation, is Shannon entropy (Shannon and Weaver [45], 1949), which states that given a discrete probability distribution $P = \{p\ i : i = 1, \ldots M\}$. Shannon entropy is defined as follows:

$$S[P] = -\sum_{i=1}^{M} p\ i\ \log(p\ i) \tag{17}$$

This formula measures the information embedded in the physical process described by P. Therefore, null entropy or enthalpy means full certainty and efficiency about the system's outcome, and entropy measures the system's random energy, uncertainty, and inefficiency.

The Chi-square tests in Table II demonstrate that there is a significant relationship between the expected and observed usage times of MIST over the Traditional RFID, after year FOUR. Table III looks at the MIST adoption variable. Lambda measures the percentage of error reduction when the independent variable (MIST usage) is used to predict the dependent variable (time). Calculation based on any desired outcome contributing to lambda assumes that lambda ranges from 0 to 1. As usual, we want significance <.050 for lambda to be statistically significant. Because time performance was dependent, MIST usage was a significant predictor. MIST contributed 31.1% ± 7.6 (SE) of the variability of time performance. In addition, time performance was a good predictor of MIST usage (sig. = .000). The symmetric value was significant, and its value was between the other two lambda values. Goodman and Kruskal's (1954) tau is similar to lambda but is based on predictions in the same proportion as the marginal totals (individual row or column subtotals). No symmetric value is given because it is only

TABLE III
MIST ADOPTION VARIABLE

			Va	ASE[a]	AppT[b]	Sig
Nom by Nom	Lambda	Sym	.289	.050	5.106	.000
		MIST Dep	.273	.041	5.988	.000
		Time Dep	.311	.076	3.472	.001
	Goodman and Kruskal tau	MIST Dpp	.171	.023		.000[c]
		TimeDep	.360	.030		.000[c]
	Uncertainty Coefficient	Sym	.295	.026	9.836	.000[d]
		MIST Dep	.248	.022	9.836	.000[d]
		Time Dpp	.365	.033	9.836	.000[d]

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on chi-square approximation

d. Likelihood ratio chi-square probability.

TABLE IV
TRADITIONAL VERSUS MIST EXPECTED VERSUS OBSERVED TIMES

Chi-Square Tests

	Value	df	Sig
Pearson Chi-Square	20.593[a]	15	.150
Likelihood Ratio	12.352	15	.652
Linear-by-Linear Association	.358	1	.550
N of Valid Cases	302		

a. 11 cells (45.8%) have expected count less than 5. The minimum expected count is .07.

directional and it predicts that both variables can be significant. The uncertainty (entropy) coefficient is a measure of association that indicates the proportional reduction in error when values of one variable are used to predict values of the other variable; both symmetric and directional versions are calculated. The proportional reduction in error was 36.5%. In other words, using MIST over traditional RFID reduced the entropy or probability that we would make a prediction error on the time performance dependent variable. Or having access to the MIST variable improved our probability of predicting the correct time performance level by 36.5%. Because the uncertainty coefficient uses the entire distribution of data to draw its conclusions, it follows that it is a good measure for reducing MIST usage entropy.

The Chi-square tests in Table IV, on the other hand, demonstrate that there was NOT a significant relationship between the use of the expected and observed times of Traditional RFID over MIST, ORIGINALLY, in year ONE. This provides a baseline to compare the usage and lowered entropy of MIST four years after adoption. Table V looks at the Traditional RFID adoption variable. Lambda measures the percentage of error reduction when the independent variable (Traditional usage) is used to predict the dependent variable (time). Calculation based on any desired outcome contributing to lambda assumes

TABLE V
TRADITIONAL RFID ADOPTION VARIABLE.

Directional Measures

			Val	Error[a]	AppT[b]	Sig
Nom by Nom	Lambda	Symmetric	.000	.010	.000	1.000
		RFID Dependent	.000	.000	.[c]	.[c]
		Time Dependent	.000	.023	.000	1.000
	Goodman and Kruskal tau	RFID Dependent	.008	.005		.695[d]
		Time Dependent	.011	.009		.845[d]
	Uncertainty Coefficient	Symmetric	.017	.010	1.683	.652[e]
		RFID Dependent	.014	.008	1.683	.652[e]
		Time Dependent	.021	.012	1.683	.652[e]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation
e. Likelihood ratio chi-square probability.

TABLE VI
SIGNIFICANT DIFFERENCE BETWEEN THE MIST AND THE TRADITIONAL RFID

Paired Samples Test

	Paired Differences							
		St	Std.	95% Confidence				
	Mean	Dev	Er	Lower	Upper	t	df	Sig
P1 Tim	-2.94	1.714	.098	-3.141	-2.752	-29.86	301	.000
P2 Dis	-3.07	1.910	.109	-3.295	-2.863	-28.01	301	.000

TABLE VII
DISCRIMINANT ANALYSIS RESULTS

Original	Count	1	192	0	192
		2	9	137	146
	%	1	100.0	.0	100.0
		2	6.2	93.8	100.0
Cross-validated[b]	Count	1	192	0	192
		2	9	137	146
	%	1	100.0	.0	100.0
		2	6.2	93.8	100.0

a. 97.3% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 97.3% of cross-validated grouped cases correctly classified.

TABLE VIII
CLUSTER ANALYSIS

Number of Cases in each Cluster

Cluster	MIST	192.000
	RFID	146.000
Valid		338.000
Missing		.000

TABLE IX
R-SQUARE RESULTS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.853[a]	.728	.726	.259

a. Predictors: (Constant), time, distance

that lambda ranges from 0 to 1. As usual, we want significance <.050 for lambda to be statistically significant. Because time performance was dependent, Traditional RFID usage was NOT a significant predictor. Traditional RFID contributed 0.00% $\pm$ 2.3 (SE) of the variability of time performance. In addition, time performance was NOT a good predictor of Traditional RFID usage (sig. = 1.000). The symmetric value was NOT significant, and its value was NOT between the other two lambda values. Goodman and Kruskal's (1954) tau is similar to lambda but is based on predictions in the same proportion as the marginal totals (individual row or column subtotals). A symmetric value is given (.695) for RFID and (.845) for time, because it is NOT directional and it does NOT predict that both variables can be significant. The uncertainty (entropy) coefficient is a measure of association that indicates the proportional reduction in error when values of one variable are used to predict values of the other variable; both symmetric and directional versions are calculated. The proportional reduction in error was 2.1%. In other words, originally, in year one, using Traditional RFID over MIST only minimally reduced the entropy or probability that we would make a prediction error on the time performance dependent variable. Stated another way, having access to the Traditional RFID variable improved our probability of predicting the correct time performance level by ONLY 2.1%, whereas having access to the MIST variable improved our probability of predicting the correct time performance level by 36.5% after year four.

Table VI demonstrates that there is a significant difference between the MIST and the Traditional RFID in terms of both time reduction and distance to communicate. MIST outperforms Traditional RFID in both measures.

Table VII can be used to show the Discriminant analysis results of classification. MIST was correctly classified 100% of the time in terms of distance and time measures. It can be seen that 93.8 % of the traditional RFID tags were correctly classified. However, 6.2 % of the Traditional RFIDs were misclassified and this lead to a Type I error of being classified as MIST performance when in fact they were within traditional RFID parameters.

Number of Cases in each Cluster: Table VIII illustrates support for the discriminant results demonstrated in Table VII. It can be seen that the KNN Clusters identified 192 MIST and 146 Traditional RFID tags in terms of distance and time. The previous Type I errors were correctly placed in the Traditional RFID cluster for a total of 338 total tags by the KNN method.

The R Square value in Table IX indicates that 85.3% of the improved MIST park and forward viscosity can be explained

TABLE X
SIGNIFICANT RELATIONSHIP

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	60.379	2	30.189	448.363	.000[b]
	Residual	22.556	335	.067		
	Total	82.935	337			

a. Dependent Variable: MIST effectiveness

b. Predictors: (Constant), distance, time

by improvements in the reduced entropy tag time and distance metrics. This is an improvement over traditional RFID measures.

Table X shows that we have reason to believe that there is a significant relationship between time, distance and MIST effectiveness. The p value $= 0.000$. Further, both time and distance contributed to the overall entropy model.

VII. Discussion and Recommendations

The Internet is a large distributed system with clients, servers and databases which add to the collection of Intranets, where an Internet service provider provides connectivity. The backbone is composed of satellite, fiber optics, and high-bandwidth circuits such as NIPR net. Transparencies are concealed from the user. The main hypothesis is that Army business processes can be optimized through automated collection and reporting of data from Mash. Yard management is one objective function of this hypothetical scenario that Metric is advocating. There are also three other areas. First, condition-based maintenance will monitor the length of maintenance and report automatically. It has already been demonstrated how this process can be used to follow vehicles throughout the fleet through usage engine codes that can quantify vehicle health maintenance. The second condition is to monitor in-transit transitions as items move through the supply chain. The third condition provides for how items are prepositioned in the yard and on boats for efficient storage.

The recommended alternative is a replacement briefing. This will be accomplished by demonstrating how the Mash system will more effectively and efficiently assess yard management prior to entering the DLA enterprise. Superior data awareness of these logistical processes will be demonstrated. This business case outlines and provides a one-page abstract and clean summary of the Mash system capability matrix. Although not everyone agrees on metrics and algorithms as the ultimate indicators of success, this business case informs decision makers that adoption of the Mash communication and logistical application will save his forward theater of operation a minimum of $10 million per year. We recommend the adoption of economic awareness and a strategic vision to foreshadow the initial startup costs of the system and have made an economic case that is an irrefutable compelling way forward for this computer-based information system by utilizing decision trees and the Markov Process. Finally, we provide a feasibility study to demonstrate the efficiencies that will follow from an integration of the Mash hardware and software that will bridge the data for enabling Army policies, procedures, and people in their quest to deliver seamless goods in stock through the supply chain. The Mash system will have an immediate impact on SCM sustainability issues ranging from improving the quality of service to safety; financial impact; risk management; environmental concern; reputation and image of the Army; ethics; and changes in regulatory and mandatory initiatives that support the Army's mission, vision, and values.

The MIST wireless Mash network for logistics applications is a combination of technology, devices, and services using a customized Mash network protocol optimized for ad hoc configuration, security, and ultra-low power. Mash is a network topology in which there may be many alternative network connections among similar devices acting as network nodes.

VIII. Conclusion

In conclusion, the key advantages of MIST as an optimal viscosity RFID system that improves fault tolerance, decreases entropy, decreases costs and decreases backorders has been demonstrated in this study. Real options theory, decision trees and the Markov process were employed to demonstrate that the MIST system has improved efficiency and effectiveness in terms of more usage time and decreased distance readings. These improved outputs are due to post conditional Bayes factors that include tags that talk to one another with reduced infrastructure required, a longer battery life, secure and encrypted communications, tags that can have sensors, and GPS that is designed for and used with the U.S. DoD. A fuzzy Kalman filter and Colored Petri Nets also contributed to this optimized solution that includes a 1- to 3-year battery life in which the system has been tested for up to a 1000-node single Mash; up to a 1-mile linear topology; two levels of security in the networking stack; a true ad hoc joining under 5 minutes; redundant gateways; bidirectional communication through Mash; a self-healing, self-configuration, 8-byte device ID; and a 4-byte network ID. In this optimal system, several networks coexist in which bridging is supported with 99.8% data delivery reliability, a 512KB file system (file transfer protocol support), and a line of sight up to a 500-foot range between two nodes.

Finally, the future project scope should include the entire MIST Evaluation Kit and that the project teams include the labor necessary to install the kits. Some of the external resources require hardware, especially for servers, roles and responsibilities of Metric technicians, change management principles from old RFID to MIST, a communication plan, a project schedule estimate using Microsoft Project and Gantt Charts and real options. In addition, there should be a risk management plan for other branches of the DoD, the Department of Education, or commercial implementation (such as FedEx). This optimal system will increase government oversight and improve equipment accountability, ease government oversight requirements for retrograde processes, and improve property accountability (the system identifies an item's location within 20 feet and therefore mitigates property loss and related administrative burden). The results will include a significant increase in asset visibility and improved operational efficiency, with near real-time visibility that replaces inaccurate in/out process scanning, identifies process friction points and trends, enables process analysis and records time of equipment at specific locations, provides accurate process and capacity tracking, and supplies process improvement validation for future operations. The proposed optimal RFID viscosity will be provided with minimal information technology infrastructure; elimination of signpost and fixed readers; a simple installation that provides a flexible, adaptive infrastructure; and immediate tag updates with tags that can be updated remotely that therefore eliminates tag removal. Other potential future improvements include a reduction in operational cost and manpower requirements, improved overall program effectiveness, and a total projected savings of $10,047,000. In addition to direct savings derived from reductions in contracted personnel, indirect savings include increased business process efficiency, less time spent correcting human error when conducting physical inventories, less time spent validating equipment location reports, and a potential reduction in financial liability investigation for property loss during the time.

Appendix of Military Acronyms

AMATS	Army Mobility Asset Tracking System
DoD	Department of Defense
ISCHMS	Integrated Supply Chain Health Manufacturing System
MIST	Military Information System Technology
NIPR	NIPRNet, the Non-Classified Internet Protocol Router Network
RFID	Radio Frequency Identification
SCM	Supply chain management.

References

[1] A. A. Larionov, R. E. Ivanov, and V. Vishnevsky, "UHF RFID in automatic vehicle identification: Analysis and simulation," *IEEE J. Radio Freq. Identification*, vol. 1, no. 1, pp. 3–12, Mar. 2017.

[2] A. E. Abdulhadi and T. A. Denidni, "Self-powered multi-port UHF RFID tag-based-sensor," *IEEE J. Radio Freq. Identification*, vol. 1, no. 2, pp. 115–123, Jun. 2017.

[3] T. Ulz, T. Pieber, A. Höller, S. Haas, and C. Steger, "Secured and easy-to-use NFC-based device configuration for the Internet of Things," *IEEE J. Radio Freq. Identification*, vol. 1, no. 1, pp. 75–84, Mar. 2017.

[4] H. Ji, L. Xie, C. Wang, Y. Yin, and S. Lu, "CrowdSensing: A crowd-sourcing based indoor navigation using RFID-based delay tolerant network," *J. Netw. Comput. Appl.*, vol. 52, pp. 79–89, Jun. 2015.

[5] X.-H. Lin *et al.*, "Balancing time and energy efficiencies with identification reliability constraint for portable reader in mobile RFID systems," *Comput. Netw.*, vol. 92, pp. 55–71, Dec. 2015.

[6] M. Tao, S. Huang, Y. Li, M. Yan, and Y. Zhou, "SA-PSO based optimizing reader deployment in large-scale RFID Systems," *J. Netw. Comput. Appl.*, vol. 52, pp. 90–100, Jun. 2015.

[7] S. Shin and B. Eksioglu, "An empirical study of RFID productivity in the U.S. retail supply chain," *Int. J. Prod. Econ.*, vol. 163, pp. 89–96, May 2015.

[8] Q. Hu, L. M. Dinca, A. Yang, and G. Hancke, "Practical limitation of co-operative RFID jamming methods in environments without accurate signal synchronization," *Comput. Netw.*, vol. 105, pp. 224–236, Aug. 2016.

[9] M. H. Kabir, J. Han, and B. Hong, "Reader level filtering for efficient query processing in RFID middleware," *J. Netw. Comput. Appl.*, vol. 48, pp. 58–70, Feb. 2015.

[10] S. Sundaresan, R. Doss, S. Piramuthu, and W. Zhou, "A secure search protocol for low cost passive RFID tags," *Comput. Netw.*, vol. 122, pp. 70–82, Jul. 2017.

[11] A. Jedda, M. G. Khair, and H. T. Mouftah, "Decentralized RFID coverage algorithms using writeable tags," *Comput. Netw.*, vol. 102, pp. 96–108, Jun. 2016.

[12] L. Tang, H. Cao, L. Zheng, and N. Huang, "Uncertainty-aware RFID network planning for target detection and target location," *J. Netw. Comput. Appl.*, vol. 74, pp. 21–30, Oct. 2016.

[13] J. Park, C. Moon, I. Yeom, and Y. Kim, "Cardinality estimation using collective interference for large-scale RFID systems," *J. Netw. Comput. Appl.*, vol. 83, pp. 101–110, Apr. 2017.

[14] T. Zhang and J. Liu, "An efficient and fast kinematics-based algorithm for RFID network planning," *Comput. Netw.*, vol. 121, pp. 13–24, Jul. 2017.

[15] Y. Lebrun, E. Adam, R. Mandiau, and C. Kolski, "A model for managing interactions between tangible and virtual agents on an RFID interactive tabletop: Case study in traffic simulation," *J. Comput. Syst. Sci.*, vol. 81, no. 3, pp. 585–598, May 2015.

[16] T. Cao *et al.*, "RFID ownership transfer protocol based on cloud," *Comput. Netw.*, vol. 105, pp. 47–59, Aug. 2016.

[17] M.-L. Tseng, J. H. Chiang, and L. W. Lan, "Selection of optimal supplier in supply chain management strategy with analytic network process and choquet integral," *Comput. Ind. Eng.*, vol. 57, no. 1, pp. 330–340, Aug. 2009.

[18] T.-P. Lu, A. J. C. Trappey, Y.-K. Chen, and Y.-D. Chang, "Collaborative design and analysis of supply chain network management key processes model," *J. Netw. Comput. Appl.*, vol. 36, no. 6, pp. 1503–1511, Nov. 2013.

[19] K. Govindan and H. Soleimani, "A review of reverse logistics and closed-loop supply chains: A journal of cleaner production focus," *J. Clean. Prod.*, vol. 142, pp. 371–384, Jan. 2017.

[20] J. A. Rodger and J. A. George, "Triple bottom line accounting for optimizing natural gas sustainability: A statistical linear programming fuzzy ILOWA optimized sustainment model approach to reducing supply chain global cybersecurity vulnerability through information and communications," *J. Clean. Prod.*, vol. 142, pp. 1931–1949, Jan. 2017.

[21] A. Kumar and S. Rahman, "RFID-enabled process reengineering of closed-loop supply chains in the healthcare industry of Singapore," *J. Clean. Prod.*, vol. 85, pp. 382–394, Dec. 2014.

[22] L. Cui, J. Deng, F. Liu, Y. Zhang, and M. Xu, "Investigation of RFID investment in a single retailer two-supplier supply chain with random demand to decrease inventory inaccuracy," *J. Clean. Prod.*, vol. 142, pp. 2028–2044, Jan. 2017.

[23] A. S. Jaggi, R. S. Sawhney, P. P. Balestrassi, J. Simonton, and G. Upreti, "An experimental approach for developing radio frequency identification (RFID) ready packaging," *J. Clean. Prod.*, vol. 85, pp. 371–381, Dec. 2014.

[24] S. Piramuthua and R. Doss, "On sensor-based solutions for simultaneous presence of multiple RFID tags," *Decis. Support Syst.*, vol. 95, pp. 102–109, Mar. 2017.

[25] J. Chai, "Reference tag supported RFID tracking using robust support vector regression and Kalman filter," *Adv. Eng. Informat.*, vol. 32, pp. 1–10, Apr. 2017.

[26] R. Y. Zhong, "A two-level advanced production planning and scheduling model for RFID-enabled ubiquitous manufacturing," *Adv. Eng. Informat.*, vol. 29, no. 4, pp. 799–812, 2015.

[27] J.-S. Song, L. Xiao, H. Zhang, and P. H. Zipkin, "Optimal policies for a dual-sourcing inventory problem with endogenous stochastic lead times," *Oper. Res.*, vol. 65, no. 2, pp. 379–395, Mar./Apr. 2017.

[28] W. Zhou and S. Piramuthu, "Remanufacturing with RFID item-level information: Optimization, waste reduction and quality improvement," *Int. J. Prod. Econ.*, vol. 145, no. 2, pp. 647–657, Oct. 2013.

[29] E. W. T. Ngai, B. K. S. Cheung, S. S. Lam, and C. T. Ng, "RFID value in aircraft parts supply chains: A case study," *Int. J. Prod. Econ.*, vol. 147, pp. 330–339, Jan. 2014.

[30] T.-J. Fan, X.-Y. Chang, C.-H. Gu, J.-J. Yi, and S. Deng, "Benefits of RFID technology for reducing inventory shrinkage," *Int. J. Prod. Econ.*, vol. 147, pp. 659–665, Jan. 2014.

[31] T. Fan, F. Tao, S. Deng, and S. Li, "Impact of RFID technology on supply chain decisions with inventory inaccuracies," *Int. J. Prod. Econ.*, vol. 159, pp. 117–125, Jan. 2015.

[32] E. Anderson, B. Chen, and L. Shao, "Supplier competition with option contracts for discrete blocks of capacity," *Oper. Res.*, vol. 65, no. 4, pp. 952–967, 2017. [Online]. Available: http://pubsonline.informs.org/journal/opre/ISSN 0030-364X

[33] S. K. Mangla, K. Govindan, and S. Luthra, "Prioritizing the barriers to achieve sustainable consumption and production trends in supply chains using fuzzy analytical hierarchy process," *J. Clean. Prod.*, vol. 151, pp. 509–525, May 2017.

[34] D. Kannan, K. Govindan, and S. Rajendran, "Fuzzy axiomatic design approach based green supplier selection: A case study from Singapore," *J. Clean. Prod.*, vol. 96, pp. 194–208, Jun. 2015.

[35] R.-J. Lin, "Using fuzzy DEMATEL to evaluate the green supply chain management practices," *J. Clean. Prod.*, vol. 40, pp. 32–39, Feb. 2013.

[36] E. Ortas, R. L. Burritt, and J. M. Moneva, "Socially responsible investment and cleaner production in the Asia Pacific: Does it pay to be good?" *J. Clean. Prod.*, vol. 52, pp. 272–280, Aug. 2013.

[37] G. Aiello, I. Giovino, M. Vallone, P. Catania, and A. Argento, "A decision support system based on multisensor data fusion for sustainable greenhouse management," *J. Clean. Prod.*, vol. 172, pp. 4057–4065, Jan. 2018.

[38] S. Maleki, R. Sawhney, H. Farvaresh, and M. M. Sepehri, "Energy efficient hybrid wired-cum-wireless sensor network design," *J. Clean. Prod.*, vol. 85, pp. 408–418, Dec. 2014.

[39] J. Bonvoisin, A. Lelah, F. Mathieux, and D. Brissaud, "An environmental assessment method for wireless sensor networks," *J. Clean. Prod.*, vol. 33, pp. 145–154, Sep. 2012.

[40] E.-J. Wang, C.-Y. Lin, and T.-S. Su, "Electricity monitoring system with fuzzy multi-objective linear programming integrated in carbon footprint labeling system for manufacturing decision making," *J. Clean. Prod.*, vol. 112, pp. 3935–3951, Jan. 2016.

[41] Y. Aviv and A. Federgruen, "The value iteration method for countable state Markov decision processes," *Oper. Res. Lett.*, vol. 24, no. 5, pp. 223–234, 1999.

[42] W. H. Fleming, "Duality and a priori estimates in Markovian optimization problems," *J. Math. Anal. Appl.*, vol. 16, no. 2, pp. 254–279, Nov. 1966.

[43] H. M. Soner, "Motion of a set by the curvature of its boundary," *J. Differential Equations*, vol. 101, no. 2, pp. 313–372, 1993.

[44] S. Bansal and M. Nagarajan, "Product portfolio management with production flexibility in agribusiness," *Oper. Res.*, vol. 65, no. 4, pp. 914–930, 2017. [Online]. Available: https://doi.org/10.1287/opre.2017.1608

[45] C. E. Shannon and W. Weaver, *The Mathematical Theory of Communication*. Champaign, IL, USA: Univ. Illinois Press, 1949.

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