The future is already here – it's just not evenly distributed.
—William Gibson, quoted in *The Economist*, December 4, 2003

ABSTRACT

Storage and Processor technology has continued to decrease in cost dramatically over the past 50 years. We are at the point that almost any natural process is possible to compute. Most dramatic is miniaturization which facilitates inclusion of instrumentation in and on industrial assets, goods and packaging.

The Cold Storage Supply Chain is replete with opportunities to improve efficiency and effectiveness in handling produce and goods. Though there are many exceptions, the current state of information processing in small to medium sized enterprises which dominate the industry is still rooted in paper and early computing technologies. It is now economically feasible to move from preventative to predictive maintenance of the forklifts, conveyors and trucks involved in moving materials within the Cold Storage Supply Chain.

The three main decision makers, CFO, Shop Manager, and Floor Manager, can all benefit greatly from this revolution.

Starting with what is doable today with existing data on Asset Maintenance, this paper describes how the well know-known method of Dynamic Programming can create an Asset (read Forklift) Economic Replacement Metric.

It uses Asset Maintenance Work Order & Fulfillment History and an Asset Depreciation Schedule to create the metric for Fleet Capital Allocation Decisions of the CFO of a Cold Storage Supply Chain Materials and Goods Movement Enterprise.

Although aircraft and space avionics introduced these methods over 30-50 years ago, they are now broadly referred to the Industrial Internet of Things.

This paper introduces how the well know-known analytic methods and technologies can now be exploited today and for the foreseeable future which is already here in spots.

Contents

Focus of this paper

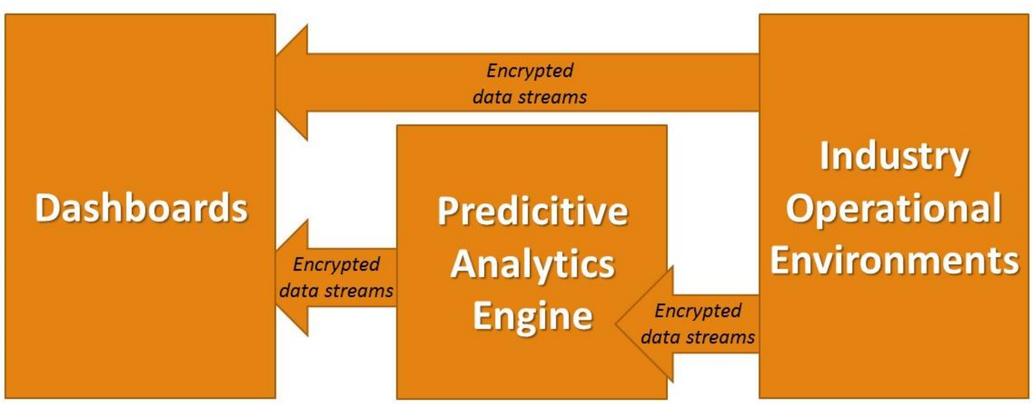
Better is the enemy of good enough
Private communication, Dan Schutzer, 1988, On banking system application readiness

The Question for us:
"What is good enough for near-time analytics to support tighter decision windows in
Cold Storage Supply Chain Management?"

The 21st Century ushered a new era of intelligent and informed business decision making[i]. The alignment of new technologies - Big Data and Big Storage and lately IoT (Internet of Things), and the new discipline of Data Science, provide for a better and faster decision making. These three elements are not only the three legs of new industries but are in the core of new ways of conducting business in old and tested industries.

From real time response to customer inquiry and optimizing handling of workloads to hands-on for the state of the business from the health and performance of the individual machine (asset) on the floor to the overall well-being of the enterprise. All this does, and will further change the way Cold Storage Supply Chain Business Decisions are made

Time critical decisions are needed from scheduling and routing shipments, to monitoring the performance of the forklifts in the warehouse and over-the-road trucks as well as containers in and between cold storage warehouses.



21st Century Supply Chain Information Delivery:
Show me the Data! Crunch me the Data!!

Business Case for an Analytics Platform in Supply Chain Management

The Situation

Makers of complex industrial assets such as aircraft and power generators have solutions in the marketplace (e.g. GE and Northrop Grumman).

However, those solutions are specific to consolidated industry verticals and cannot be easily adapted to the fragmented markets.

OEMs of industrial assets have "closed platform" solutions tailored to their product set.

However, those solutions are not extendable to other brands and lack objective analysis comparing brand performance.

The Opportunity

Data Analytics have yet to be fully applied to Industrial Asset Management

As most warehouses use assets from multiple OEMs, what is needed is an open platform to create open and standard decision processes across a fragmented and consolidating industry. Premium Value is commodifying rapidly. Sustainable value can be extracted by tracking and following the wave.

- In our first industry vertical, 15 Million Forklifts have at least 5 failure/preventive maintenance events each year.
- For example, the ability to monitor and predict the next part failure can save industry verticals $100s of millions.
- Annually, from our initial estimates, forklift maintenance is a $4.0 B maintenance industry. Eliminating only one failure event per asset per year will save the industry $800 MM.
- The fixed cost of taking many industrial assets off-line for repair greatly exceeds the marginal cost of the next repair.
- Other industrial asset categories have similar profiles.

Industrial Internet of Things—IIoT in Supply Chains

Goods and produce and commodities (Work Load Things) are moved from origin to many destinations. Equipment (Things Moving Things) are operated within warehouses, over-the-road and on-the-shelf (Venues among which Things move and occupy. The Things include not only the workloads and the mechanisms used to fulfill them, but also the infrastructure and environment of the Supply Chain.

In IIoT, we name, tag and monitor Things at very granular and macro levels. Not every grape, ear of corn or grain of rice are tagged, but containers of them are identified and tracked. In wine making it is from the Vineyard to the Barrels to the Bottles to the Store. In berry growing, it is from the Field to the Distribution Center to the Store. It is nano-pico-femto to giga-tera-peta level of automation. The scale is 10^{-15} to 10^{15} (and beyond) of measurement and tracking metrics.

The multitude of Things are able to produce Data Points at sub-second levels into The open Internet and many dark networks subsumed.

The IIoT is awash in great seas of data moving in many currents (Data in Motion) and ending in large and deep lakes (Data at Rest).

This is IIoT Big Data.

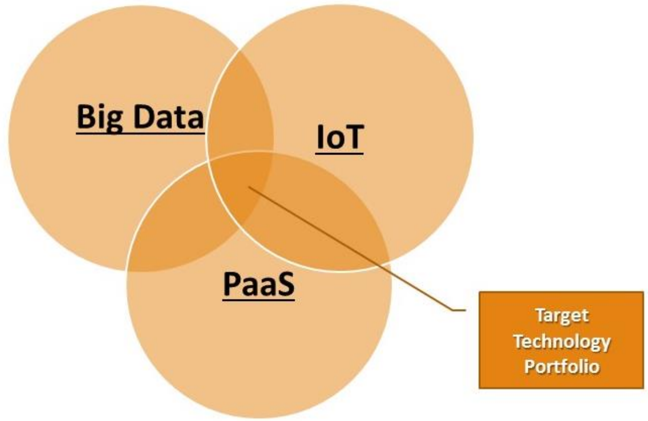
Current Information Technology Maturity

Yaba-Daba-Do

Seriously, much of the Forklift Industry is still on paper and DOS-like apps, especially smaller operations. Manufacturers are moving to IIoT SaaS applications. But these are walled gardens with little fungibility among Forklift operational data processing systems.

It is a rapid evolution to reach the 21st Century. We must stand up and free our hands, engage our minds.

Supporting Technology Trends for 21st Century Supply Chain Management



IoT: Internet of Things

Connecting to smaller and smaller physical devices.

- Small Cheap Sensors and Processors

  Semiconductor and Nanotechnology is getting to the atomic level, and in some cases, subatomic.

- Ubiquitous Cheap Communication Access

  Despite telecommunication consolidation, or maybe the cause of it, commodity pricing pressure persists with premium made from bundling services like Comcast does

Big Data

Methods for capturing and analyzing very large streams of structured and unstructured data.

- In-Line Industrial Strength Data Cleansing Methods

  Everyone knows autocorrect and Google suggestions. IBM, KPMG and others each do 100's of millions and billions of annual business supporting all industries in building and maintaining authoritative data bases. Despite the belief that large number data trends can withstand significant error, most businesses strive to create as much clean and accurate data as possible.

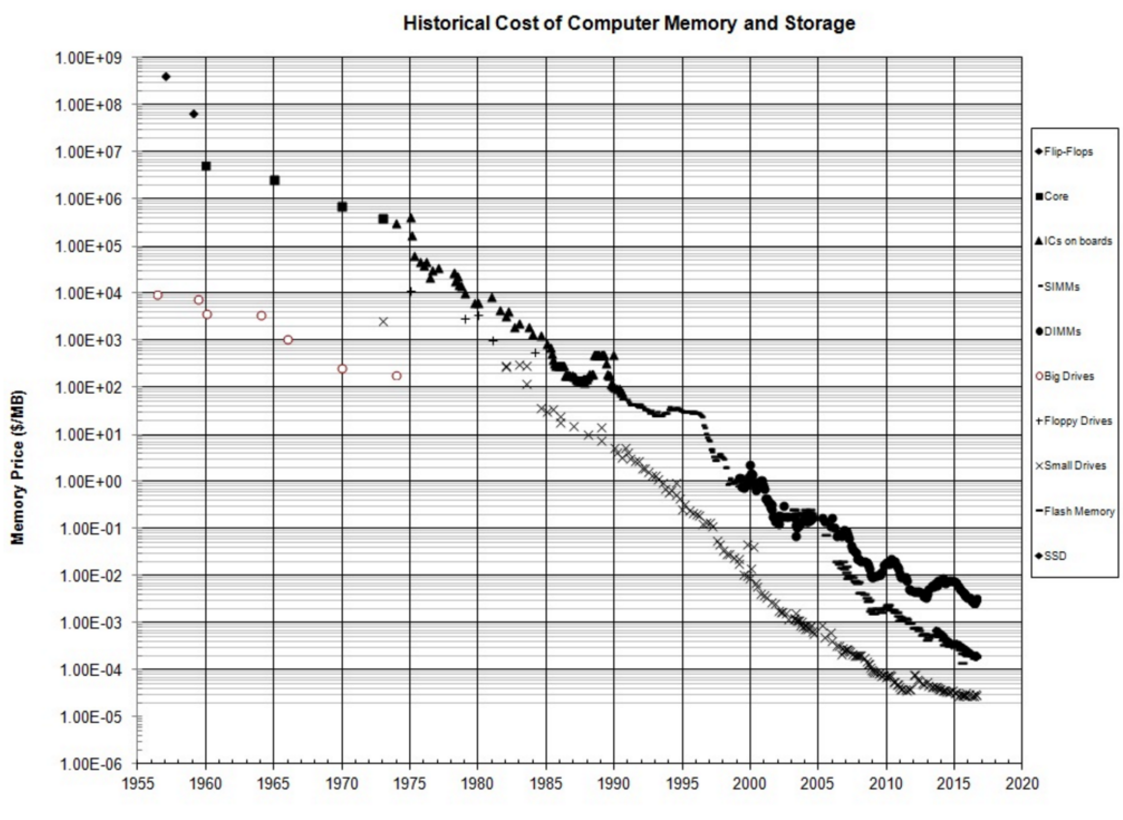
- Cheaper Storage, Bandwidth & Processors

  From detailed 2013Q3 study for a Fortune 50 company one author did: "Storage cost is halving every three years. A 10-Terabyte System from SiSense can crunch that in 10 seconds. This system can capture and contain all of the TwitterVerse for two weeks—all for less than $100,000.

A 4-Terabyte Raid box is $250 from G-Raid." Projecting to 2016Q4, two-week TwitterVerse can be stored for $10,000 and a consumer grade Four-TB RAID device can be had for $125.

The above statement is based on the 60-year graph below. It looks like same trend down with just a slight slow-down in small devices where the containing access mechanism becomes a greater portion of the cost:

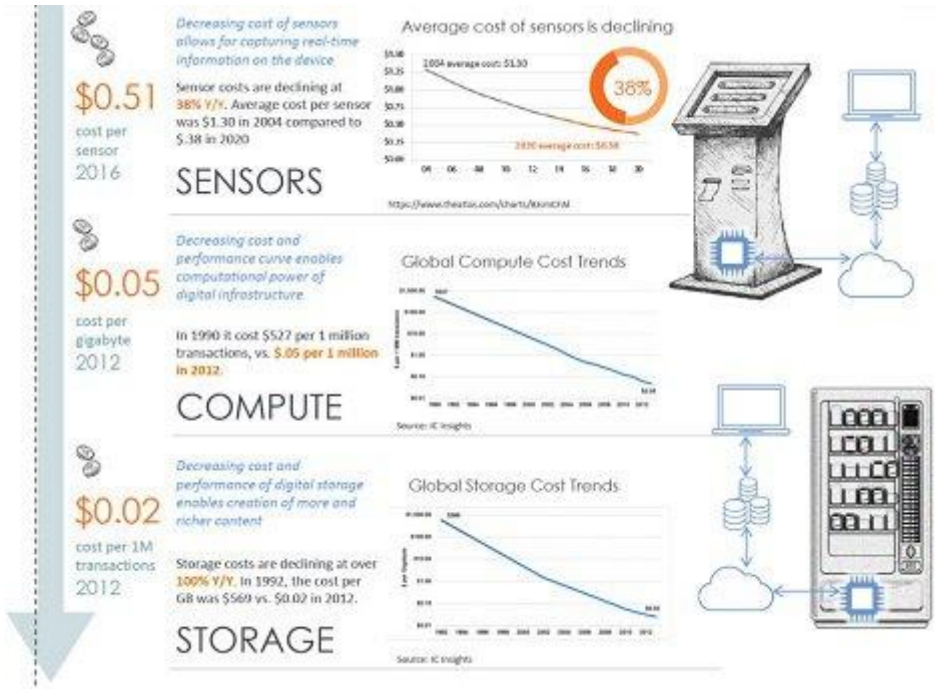
Graph of Memory Prices Decreasing with Time (1957-2016)



Bandwidth cost is dropping in a similar fashion with Terabyte WiFi on the horizon.

Similarly, processors are still dropping according to Moore's law as the technology has created 3D circuitry. The IT Economics of IoT are detailed in http://iot.sys-con.com/node/3951895.

A very descriptive graphic is provided in this article:



- Data Science as Professional Category

  Data Science courses abound in virtual curricula MOOC’s and from prestigious university graduate programs such as MIT, Berkeley and Columbia, to name a few. For motivation of a professional category, from www.datasciencemasters.org, we have the opening statement:

  > We need more Data Scientists.
  >
  > ...by 2018 the United States will experience a shortage of 190,000 skilled data scientists, and 1.5 million managers and analysts capable of reaping actionable insights from the big data deluge.
  >
  > -- McKinsey Report Highlights the Impending Data Scientist Shortage 23 July 2013
  >
  > There are little to no Data Scientists with 5 years of experience, because the job simply did not exist.
  >
  > -- David Hardtke "How To Hire A Data Scientist" 13 Nov 2012

PaaS: Platform as a Service

Cloud-based environments that promote and support individualized specialized capabilities.

- Hybrid Clouds are the mainstream vanguard

  A Cloud is a uniform standard set of commodity capabilities for constructing networks of devices connected to data centers. Private Cloud is totally out of the Public Cloud. Hybrid is the controlled use of both together.

- Walled Gardens (environments where users are held captive) of Infrastructure as a Service (IaaS) and Software as a Service (SaaS) need to be bridged

A Platform is an architecture and tools to build SaaS's on IaaS's with that architecture within a known infrastructure.

Consider these three trend areas a little deeper, one at a time.

Industrial Internet of Things, Massive Streams of Data—Forklift Edition

Our focus here is on Industrial Assets and the Internet of Things. For the sake of argument with our further focus on forklift trucks, we assume at least 15 Million forklifts in the world.

This is an estimate from reports that the top 20 producers of forklifts produced about 1 Million lifts in 2013. Assume an average life of 15 years per lift. This is a conservative number as our research has identified lift trucks in active fleets for 20 years.

Imagine a world in which every forklift produces a payload of data on its operation every second. In each data payload, there would be attribute values totaling 40 bytes:

- Identifier
  ipv6 address: 16 bytes (10^{38}—100 Trillion, Trillion, Trillion different values)

- Location
  GPS coordinates, 2 signed floating point: 8 bytes

- Temperature
  In Kelvin, 1 floating point: 4 bytes

- Vibration
  Cycles per second, integer: 4 bytes

- Fuel Level
  Type, Level; Voltage/Petrol/Natural Gas (1 byte), value in appropriate units (3 bytes): 4 bytes

- Fork Position
  Percentage from the bottom to the top position, floating point: 4 bytes

Thus, assuming each lift truck produces, one report per second of operational data streaming is per truck in operation:

- 40 bytes/second
- 2,400 bytes/minute
- 144,000 bytes/hour
- 2,304,000 bytes/day (assuming 16 hours)
- 460,800,000 bytes/year (assuming 200 days)

The Internet of Things Stack—Processing the Data for Business Value

How will the Data be captured and processed into Information yielding Knowledge? What are the layers of processing?

We offer this diagram to show the separation of concerns in IoT. We start in devices, e.g., Forklifts and their Components operating in the Real and Virtual Worlds. Data from these devices are sensed, captured, filtered, enriched and arranged to be representative operational profiles of surrogate digital objects.

These operational profiles inform the Business Processes for measuring and managing flows and decisions that can be optimized to create Business Value. This Business Value is Knowledge leading to Sustainable Reduced Costs and Predictable Increased Revenue.

This diagram is a guide for organizing data streaming and processing technologies and locating these technologies in layers from Real Device up to Business Process.

An Internet of Things Technology Stack

This IoT Stack is an architectural depiction of the infrastructure moving information, data and events, up into the application areas. It is all moving to Assembly of specific Business Capabilities (not de novo Construction) that create Significant Results for the Enterprise.

First thing to notice is the Network Edge contains all the connected devices required to interact with the Network Interior. This interaction is done via the Distributed System Backbone Overlay.

The Network Edge connected devices “talk” via Protocols that send data through Data Profiles that filter the Data Streams into and out of the Orchestration Delivery mechanisms connected to the Backbone.

Inside the Network Interior and Network Edge, a vast pool of Surrogate Device Agents maintains the relevant states of the Real Devices. These Surrogates provide the inputs and outputs of Tasks that ingest and produce information for Work Flows. The Work Flows realize the Business Value of the Business Processes that maintain Books and Records of Transactions, produce Feedback to control the Devices, as well as providing grist for Business Decisions for analysis that leads to controlled costs and improved revenues.

Big Data

Big Storage

How Big is Big?? How do we get our head around the size of Things and their Data generated?

A 100-yottabyte (yottabyte = 10^{24} bytes) data cache is equal to about 130,000 Trillion (10^{12}) data CD's. One data CD holds about 768 MB (10^6) and is 1 mm (10^{-3}) thick (like a US dime). For physical scale of this quantity, 130,000 Trillion CD's stacked up (130 Billion km) would make a plastic tube that runs about 435 roundtrips from the Earth to the Sun (150 Million km).

A 100-yottabyte capacity data center is being built in the desert of Utah for some unnamed agency.

Information Utility in Big Data

Fundamentally, the information utility in Big Data turns on the Statistical Principles of Correlation and on The Law of Large Numbers where even the subtlest of mean dependent behavior can be detected reliably and with confidence. With computing power today, we can model (calculate) very quickly these phenomena derived from massive amounts of data. This is the province of Predictive Analytics and underpins an enhanced Business Intelligence strategy.

Gartner has some valuable insights on choices for Analytics for Data Warehouses and Data Management:

> "Disruption is accelerating in this market, with more demand for broad solutions that address multiple types of data and offer distributed processing and repository options"

Accordingly, they provide their ever popular visual, the Magic Quadrant:

These vendors provide more of a platform for Big Data and Data Management than one for Analytics.

Predix from GE is an Analytics Platform (a cloud-based environment to develop bespoke Analytics Service suites) built to run best in the Microsoft Azure cloud, but available on AWS cloud as well.

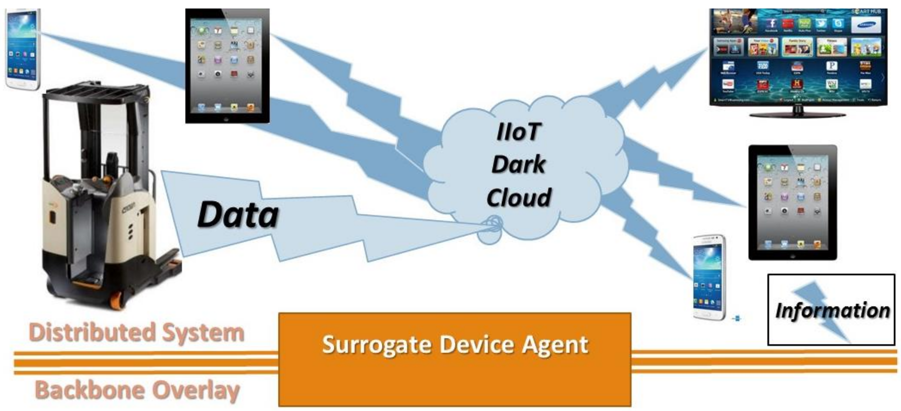
Both Azure and AWS have IoT infrastructure interface services. Alas, these services aren't interoperable. However, Predix has services which are portable between these clouds, but not interoperable without a layer of translation veneer.

Volumes of Big Data Streams and Information Delivery Pathways

Look at a Forklifts that is instrumented to provide periodic Data Payloads per the discussion above on Page 10.

The pattern of this data generation is straightforward.

Each Forklift sends a Data Payload into the Cloud to be condensed into Information that emanates about that Forklift and its complete operational history.



Data Flow and Information Delivery

For example, operating by the above pattern at producing 460.8 MB (10^6) per 200 days per forklift, 10,000 forklifts yield 4.608 TB (10^{12}) of data to process in a year.

Assuming an average life of 15 years, these 10,000 Forklifts produce 69.12 TB generated 40 bytes per second from each Lift.

In current Solid State Drive (SSD) technology, 70 1TB SSD drives stacked on top of each other would be a volume that is a little over 2' high X 2.75 " wide X 3.75" long.

At current retail pricing, the 70 1TB SSDs would cost $31,500 or $3.15 for each Forklift's historical data, $0.21 per year of useful life. In wholesale numbers, it would be about half that—very affordable!

Platform as a Service (PaaS)

A Platform as a Service is

1. An Architecture
2. with Tools to develop multi-tenant Software-as- a-Service (SaaS) instances consistent with said Architecture
3. and, Interoperable within and among Infrastructures-as-a-Service offerings.

The most widely known successful Software-as-a-Service is Sales*force* which is a Cloud-based (Web-based) Customer Relationship Management application. Since 1999, having left Oracle, Marc Benioff has built this enterprise into a $55 Billion valuation with $6.667 Billion 2016 revenues, 25% increase from 2015.

In addition to an aggressive acquisition strategy, Sales*force* introduced Force.com a Platform-as-a-Service that exposed the toolkits they used to build their SaaS. This was done shortly after Benioff became CEO in 2001. They marketed it aggressively using acquisitions to enhance the usability and by 2009 had IDC produce an eloquent PaaS Business Case paper for them. The case is fourfold better-cheaper-faster:

- Faster Time to Market
- Lower Cost
- Higher Quality
- Better Performance

Predix from GE is a PaaS for building analytics for Industrial Assets. It is largely horizontal. GE is promoting a developer community to create vertical solutions on Predix. The Predix PaaS promises the same better-cheaper-faster characteristics as Force.com.

We can construct Predictive Analytics Services on this PaaS in such a way, it is easily portable to the most cost-effective IaaS available. The point is we can start with Predix as our Canonical Services Reference Behavior.

Dive down a little deeper into this Internet of Things Architecture.

The IoT Architecture Stack

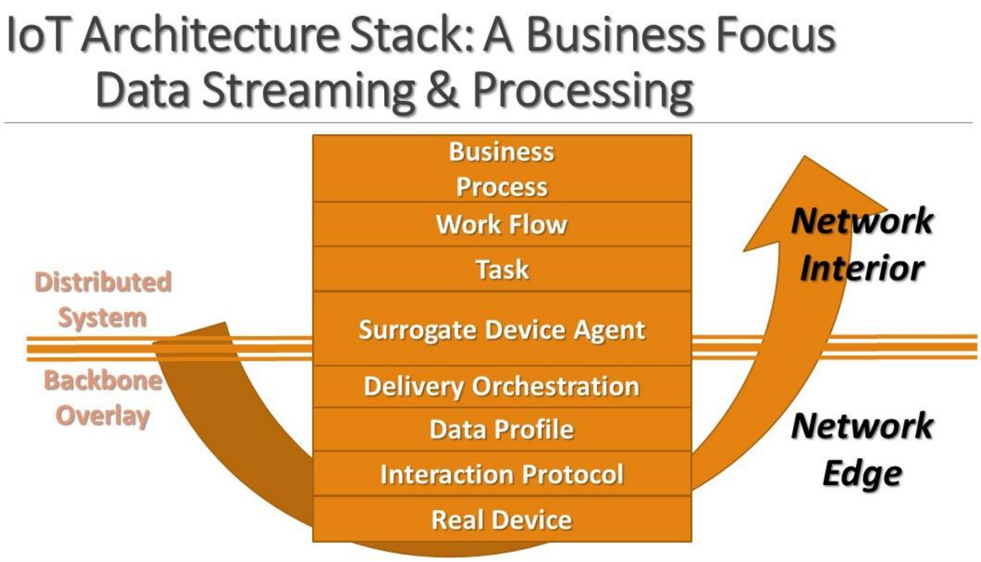
This is a TCP/IP-OSI stack approach: Layers, more virtual than actual. It is a Separation of Concerns approach.

Premium value is garnered up the stack, above the Line (Backbone), mostly.

Be Fast to Market.

Commodity value is found down the stack, below the Line, for the most part.

Be Big in Market.



The IoT Stack, Bottom Up

[See the Appendix for a deeper discussion of this section.]

As said above, this IoT Stack is a depiction of the infrastructure moving information, data and events to and from the Network Edge and Network Interior.

Building it is all moving to Assembly, not de novo Construction) of specific Business Capabilities that create Significant Results

The Commodity Layers

There are many objects and processes that are so ubiquitously implemented and available that dealing in them requires large scale to be competitive. These are IT Commodities.

Industrial Assets are almost all Commodities. Sustainable Premium value is derived from superior performance against competitive products.

Any Premium IoT benefit derived from these Industrial Assets must be extracted much further up the stack unless a manufacturer can capture and retain their customers within a walled garden.

Device

Devices come in all shapes and sizes with many purposes and capabilities. They are the Things of the Internet. They have names and descriptions which, when defined precisely, define a subset of the Internet that can be operated securely and efficiently.

Interaction Protocol

Interaction Protocols are the way devices "talk" to the world. They have several modalities of operation: people-machine, peer-peer, machine-machine, either in a standard or in a proprietary manner.

Data Profile

List of data attributes, their structure (cf. Appendix Data Profile) and formatting. In tech terms, SQL-like.

Delivery Orchestration

This layer represents Process Automation at the Network Edge, data Postcards from the Edge.

The Network Mesh Connection (Enterprise Backbone Overlay—EBbO.

For the past 30 years, we have been moving towards full featured People-Machine, Peer-Peer, Machine-Machine Communication Middleware and Nodal Connections.

Surrogate Device Agent

This is the layer of Persistence and Driver Objects for all Devices, where all the Intelligent Agents of the Network reside.

The Premium Layers

Premium objects and processes are how Enterprises build distinctions worthy of special valuation above competitors. They are concentrated in these layers.

Commodity objects and processes exist in the Premium Layers as well. Unique combinations of Commodities can produce very Premium results.

Premium areas are best illustrated by an Exemplary Business Process: Determining Capital Requirements from Turnover of Fleet Assets

Task

Tasks are the individual work steps needed to achieve the eventual result desired: calculate Asset rankings.

Workflow

Workflow is the sequencing of Tasks to get to a business end-result. Load Environment with base data.

Business Process

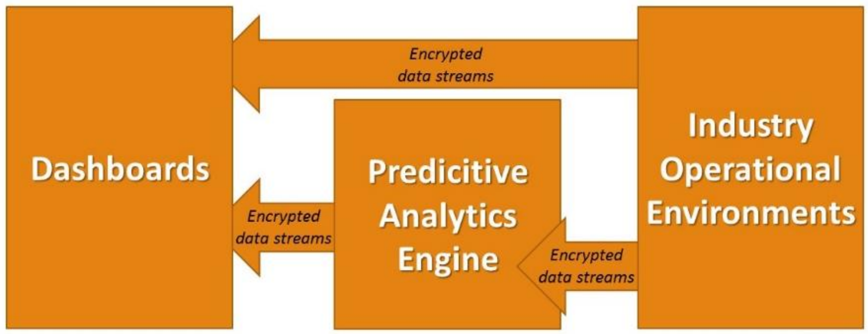
A Significant Business Activity is Treasury Operations: Balance Sheet Management, a specific Business Activity to minimize Capital Demands.

Predictive Analytics

We are very good at Reactive Analytics to measure and improve what actions we *did*.

How can we measure and improve what actions we *might do*?

This is Predictive Analytics with Monitoring.



21st Century Supply Chain Information Delivery:
Show me the Data! Crunch me the Data!!

How does it feel?

Reactive Analytics vigorously pursue focused Data Collection in concert with Better and Better Metrics.

Predictive Analytics shift actions forward in time with scoring of possible responses. It is Space and Nano Science.

It's 21st Century Operations Management—trickledown technology from 30 years of financial quants and oil exploration. Now we call Quants, Data Scientists. So, like Quant Fund Management, will we have Data Science Funds? We already do—Just greater volume, more precision! Engineers like Archimedes are valuable, but either hard to find or too many depending on who you talk to. It is not easy!

We position towards Data Engineering for Forklift operations, Information Delivery for all Supply Chain managers—Shop, Floor, CFO—and Knowledge Sharing as close to real-time as possible to fitness for purpose. Predictive Analytics Services can help all of them.

What are the Decision Portfolios where Predictive Analytics Services can benefit immediately?

Manager/*Decision*	**CFO**	**Shop**	**Floor**
Primary	Treasury	Repair & Parts Inventory Management	Logistics & Goods Inventory Management
Supporting	Capital Asset Allocation	Optimum Distributed Parts, & Quickest Time to Repair	Best Current Asset to Deploy for Workload in a Unique Environment
Environment	Financial Metrics	Failure Metrics	Operational Metrics

Remember the Secret Sauce of 21st Century Industrial Asset Management:

> *Keep your information current. Rank actions by positive expectancy.*

This Strategy is how Susquehanna Group, in less than a decade in the 80's, grew $1 Million into $1 Billion positioning in options, index and futures markets. We can apply it to Industrial Asset Management as well to great advantage.

Whitespace Opportunity

We believe that there is a tremendous whitespace for Predictive Analytics Services in the emerging small Asset Internet of Things in Supply Chain Fleet, Refrigeration and Conveyance Management. It starts out as a Long Tail Strategy, but moves to consolidation by shortening the Tail quickly.

In fact, it is consolidating at this moment. Manufacturers are recreating branded parts sales outlets by decommissioning independent parts dealers.

The driver of exploitation of this whitespace is Data Science.

Data Science is not all that new! In the past 30 years, techniques have been developed and refined while costs have dropped so dramatically. Thus, more and more marginal markets become profitable.

Data Science

Morphing Data into Information to build bodies of Knowledge from which to extract Wisdom.

Emergence of a "New" Discipline

Data Science is an amalgamation of probability & statistics, operations research and computer science. It deals with structuring and analyzing the behavior of very, very large data bases and streams of data. Nothing is new, just a designated set of techniques and subject areas of focus from these three disciplines.

When dealing with $10^{15\text{-}21}$ of Things and Data Points of those things, we are in the realm of very, very large numbers. We can discern very subtle behaviors and patterns with Methods developed using the body of Probability and Statistics. And now with Methods from Computer Science in Machine Learning (Since we use computers to implement, it is all machine learning and teaching.)

Predicting events/behaviors is a center piece of Analytics—states/conditions that evoke/precipitate significant outcomes.

Going Deeper

Data Science is the practice of using quantitative methods to turn data into valuable information that can be applied to make better informed decisions. An amalgamation of methods from disciplines such as Statistics, Artificial Intelligence and Computer Science combined with cheap storage and cheap computing, Data Science furnishes business with the ability to make sense of the avalanche of data and steer its activity.

The analytical process that Data Scientists engage spans from accessing data sources to retrieve data and manipulating it to the desired format and structure to applying analytical methods to distill insight into behavior and patterns and communicating the results to users to assist in their decision-making processes.

Sources of data have been broadened to include many new types of data never been a subject of analysis before. Data logs, news stories, sensor data, social networks chats and messages all contain valuable information about trends in public mood and consumer taste, the mechanical integrity of a machine, and much more. New methods were developed to manipulate these new forms of data, and new analytical methods where harnessed to analyze growing quantities of multidimensional data.

What is a Thing: Structure of a Prediction Base for a Business Purpose?

We need to get precise about a Thing that we wish to Define, Track, Measure and Manage. Predictive Analytics are a key tool for 21st Century Enterprises: Measure and Improve Performance.

Predictive Analytics ingest the vast myriad of Datapoints on Some Thing on the Internet. These Datapoints are used to track and measure behavioral patterns of That Thing.

A formal definition of this concept is "simple" in structure: four primitives to understand.

1. Thing
   An object or place, like an axle assembly on a forklift on a warehouse floor

2. point-in-timespace
   A moment of observation, like 10 times a second:
   When: <meter>
   Where: <geo position>
   What: <heat dissipation> ><vibration><energy level>

3. attribute name
   A characteristic available

4. attribute value
   A countable, measurable datum

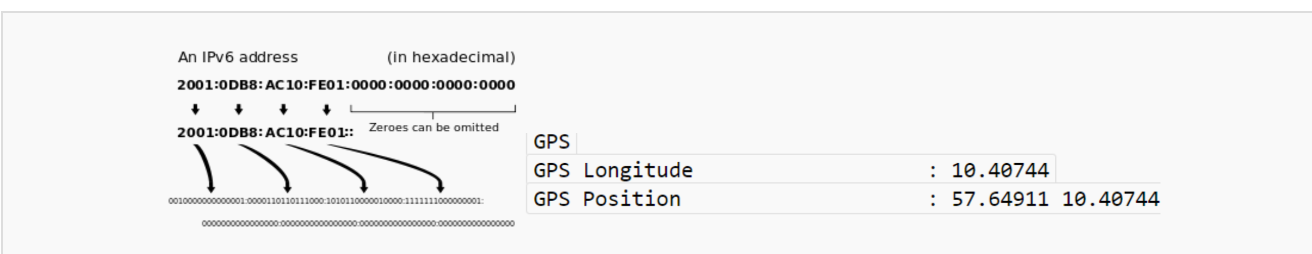
The First Step: The Fundamental Ontology of Thing (FOoT)

This is the formal Structure of the Datapoints:

{ (<thing><point in time-space><attribute name><attribute value>)* }*

Explanation of the FOoT

The objects in a, IIoT Systems conforms to a structure: <thing>, like a Forklift and its component parts, produces data periodically at <points in time-space>, like every second as it moves through a warehouse floor. These data have <attribute names>, like asset identity and location, and <attribute values> like ipv6 address and GPS coordinates:



Each "<thing><point in time-space><attribute name><attribute value>" is iterated any number of times and collected into a data set. The data sets are iterated across all <types> of <things>.

In the following section, we will briefly review some of the more prevalent concepts and disciplines in the core of the field and the problems they are intended to address.

Common Methods of Prediction

Relationships

Systems are complex structures with many moving parts and external factors that affect their behavior. Whether a social, economic or mechanical system there are things that we can influence, directly or indirectly, and measure their effect on certain measurable outcomes. Whether we assess the effect of promotion campaign on sales, or weather patterns on wild life population, we can make such assessments and draw conclusion by evaluating the relationships, between certain stimulus and its impact.

A common term for relationship is Correlation, correlation is positive when things are moving in the same direction, and negative when moving in the opposite in direction. Correlation can be representing a causal relationship, when a directly or indirectly affects B. We can say with confidence that a machine will fail more frequently as it ages and as it is used more hours per day. Other factors can be in play to determine the frequency of failure, temperature and humidity in the operating environment, type of tasks performed etc. These kinds of associations are derived using Regression Analysis

Another form of relationships is not causal but coincidental. If one likes Beer, he may also like chips and Salsa. If you liked movie A you may also like movie B. This kind of association is discovered usually by specially designed Association Rules methods. For example, finding such an association between parts failure 'if a certain part X fails it is likely that another part Y will fail at the same time or soon after' can drive maintenance and repair protocol with significant savings in labor and machine down time.

Visualization

Visualization of data, in particular big data, became a critical tool to gain and communicate insight into system behaviors. Trends, associations, and other patterns can be easily discerned using the proper plotting methods. A slew of visualization tools with broad selection of types of graphs, developed in recent years, enable analysts and user review, analyze and accentuate properties of interest. Real time visualization of streaming data from sensors or other sources of data assists in monitoring a system and raise red flags when condition approach critical levels that need immediate intervention.

Machine Learning

Within Data Science the discipline of Machine Learning is a branch that spans methods from artificial intelligence combined with algorithms founded on the foundation of statistical and probability theory. While statistics focuses on the description and inference of a population characteristics. Machine learning is about attaining insight and extracting predictive power from data.

Classification

Classification is the problem of sorting things into groups or classes of individuals that are similar to each other while different from members in the other groups or classes. Identifying populations of individuals that are susceptible to certain problems or a group of products that performs exceptionally under certain condition can be very beneficial in the capital investment decision process. Regression analysis usually separates populations into two groups of below and above the line (or plane in the multi-dimensional case)

Cluster Analysis

Another technique that can divide the field into multiple groups by different characteristics. Members of the group are similar to each other and different from members of the other groups. Different algorithms use different measure of similarity or distance to draw the boundaries of such groups. Clustering algorithms are considered semi-supervised algorithms some can work with labeled data or unlabeled data for training.

For example, given a broad array of choices of makers and models to equip a warehouse one may reasonably assume that certain makers and models are more durable and more suitable than others to operate in extreme heat, cold or humidity environments. Cluster analysis on operational history identify the most significant factors that affect the performance and durability to operate in different type of environmental conditions.

Different methods are applied to find an association of an individual to a group in a manner that can allow one to predict behavior to a degree of confidence, or learn behavioral patterns through observation over time of large amount of data to synthesize a model. The first types of tasks are usually called supervised learning where analysts navigate the process to find most adequate model. The second type of tasks are usually called unsupervised learning where the computer, in the right framework and algorithm, is left to learn on its own.

Models are built and use data to learn and improve themselves to produce better and more reliable results.

Neural Networks

Artificial Neural Networks (ANN) initially introduced by Dr. Robert Hecht-Nielsen in early 1980's was defined by him as *"...a computing system made up of several simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs."* After a short honeymoon in the 80's and early 90's in which Neural Networks attracted attention it faded somewhat until recent years where it reappeared under the banner of Deep Learning.

A Neural Network consists of many simple, connected processors called neurons, each producing a sequence of real-valued activations. Input neurons get activated through sensors perceiving the environment, other neurons get activated through weighted connections from previously active neurons. Some neurons may influence the environment by triggering actions. Learning is about finding weights that make the NN exhibit desired behavior, such as recognizing an object, or operating a machine and responding in real time to operating conditions. Depending on the problem and how the neurons are connected, behavior may require long causal chains of computational stages, where each stage transforms the aggregate activation of the network. Deep Learning is about accurately assigning weights across many such stages.

Neural Networks are suitable to learn patterns and be trained to respond in adequate manner. Sensors installed in a piece of equipment broadcast information about temperature, pressure, vibration or other physical aspects of the operating machine. This information flowing through a Neural Net model can be interpreted to alert operators when the machine is approaching critical level and trigger or recommend appropriate measure.

Bayesian Models

Bayesian models are an evolving field of reasoning and inference using network of related factors with a set of weights, measures of belief, defining the type and strength of relationships. Using processes built upon the Bayes formula and its derivatives the model is learning, updating the weights, and making inference about aspects of the model given inputs from others. Bayesian models are used in a broad range of fields from law and medicine to engineering and risk management. Trouble shooting a problem in a piece of machine or evaluating the risk of a business entity based on its financial reports.

For example: Diagnostic Bayesian Model can be created using design documentation and the knowledge of diagnostics experts. Furthermore, there exist learning algorithms which allow us to create the Bayesian Model entirely from repair records or by refining an approximate model created from documentation and expert's knowledge with the data from repair records. The user or system queries the Bayesian Model for the probability of a component defect given known observations. The model computes probability based on previous experience of the causal effect of the observation captured in the weights on the arcs between the nodes. A system or a person can decide to recommend corrective measure if needed.

Forecasting

Forecasting is a statistical discipline usually used to determine future direction and trend from historical data. If you need to estimate value of a business aspect at a point in time, or natural phenomenon usually forecasting method is used deriving trend and slope and sometimes seasonality from a time series of past values. Forecasting the demand for goods or products is what business does to plan its production resources for the next month quarter or year. Supply Chain environment provides ample opportunity to apply forecasting methods, from setting up proper inventory levels of spare parts for the equipment used in the warehouse, to multi-year capital investment plan to meet growth in future demand.

Areas for Cold Storage Supply Chain Analytics

What are the Decision Domains of the Business?

There are at least five domains in which to make decisions:

1. Warehouse Yard, Dock, Floor, Storage
   What are the environmental venues for storage, transference and conveyance of goods?

   What are the key characteristics of each venue? What behaviors are we tracking, ranking and measuring?

2. Maintenance
   What is the impact of predictive suggestions rather than preventive maintenance schedules?

   How often and under what conditions will parts fail? How will parts fail together or in sequence in close time proximity?

3. Inventory Management
   What goods and parts are stored and maintained in the Venues?

   When should parts be reordered? What parts should be stocked and at what levels? What is shelf life of perishable goods? What are the levels of classical inventory management controls?

4. Transportation
   What is the Decision Windows for Conveyance of Goods/Produce and Assets?

   What are the best transport routes based on time, traffic and road conditions?

5. Capital Allocation for Assets
   What are efficiency methods for Non-financial Capital Management like Operating Asset Economic Replacement Point?

   What are the expected levels of fleet capital management? At what intervals should Assets be Repaired, Replaced, or Redeployed?

In the detailed example two sections below, we consider Domain 5—Capital Allocation Process: Fleet Economic Replacement for a selected fleet of Crown Lift Trucks in a specific warehouse.

But first, take a next level dive into the five Decision Domains above.

Warehouse Yard, Dock, Floor, Storage

What are the environmental venues for storage, transference and conveyance of goods?

What are the key characteristics of each venue? What behaviors are we tracking, ranking and measuring?

Performance of lift trucks can be affected by environmental factors like surface, temperature, humidity and volatility of said same.

Maintenance

What is the impact of predictive suggestions rather than preventive maintenance schedules?

How often and under what conditions will parts fail? How will parts fail together or in sequence in close time proximity?

Performance of a Shop is based on how little the lift trucks spend there. Shops can be separate from or located on the Floor. How virtual can we go?

Inventory Management

What goods and parts are stored and maintained in the Venues?

When should parts be reordered? What parts should be stocked and at what levels? What is shelf life of perishable goods? What are the levels of classical inventory management controls?

Performance for Distributed Inventory must accommodate location (Floor, Shelf, Truck) and movement (Requested, Scheduled).

Transportation

What is the Decision Windows for Conveyance of Goods/Produce and Assets?

What are the best transport routes based on time, traffic and road conditions?

Performance of Conveyance is highly dependent on roads, weighing stations, construction sites, and Fleet Health.

Capital Allocation for Assets

What are efficiency methods for Non-financial Capital Management like Fleet Economic Replacement?

What are the expected levels of fleet capital management? At what intervals should assets be redeployed, repaired, or replaced?

Life Cycle of an Asset

Each stage in the figure below is an opportunity area for focused analytics to support improved decision making on Redeploy, Repair or Replace.

21st Century Pattern: Economic Stages in the Life of an Asset

- Acquisition: Funding + Transaction
  This is the largest Capital Allocation decision, generally needed to be known 18-24 months in advance.

- Maintenance: Parts + Labor
  This is the ongoing operational requirements, budgeted at least quarterly. All-in costs need to be considered: Wages + Benefits and Cost of Carry for Parts Inventory.

- Opportunity Cost: Lost Business
  This involves lost or delayed work due to failures of Assets. A forklift failure on the warehouse floor not only slows the completion of its workload, but frequently interrupts other forklift movements down the blocked aisle.

- Cost of Capital: Depreciation + Financing
  This represents the steady loss of Asset value due to age plus the requirement to finance the Capital allocated to funding the Assets.

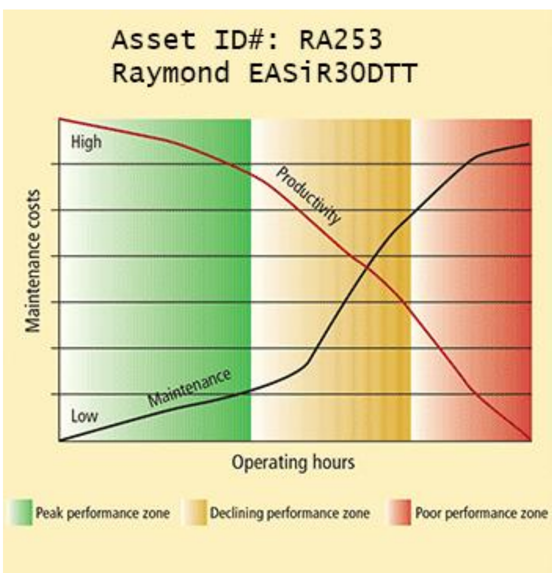
- Cost of Disposal
  This refers to the removal of Assets from production and what is involved in selling or scrapping the Assets. It could be as little as allocated rent for a salvage yard where assets may be kept.

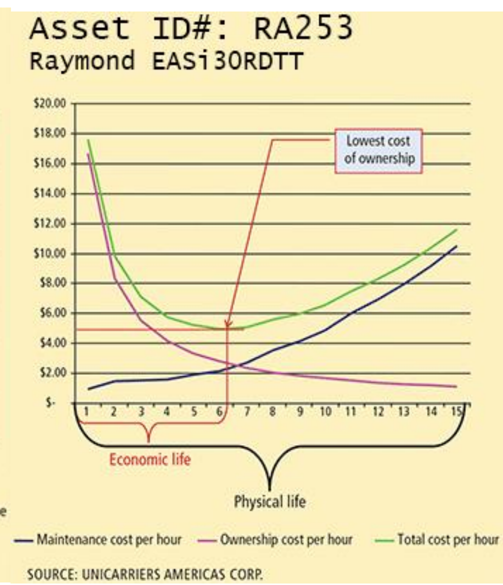
A Detailed Example Overview

From 2014-16, we analyzed 20 years of maintenance on forklifts from a client of www.hettingerinc.com. A set of 1 Yale, 2 Crown and 17 Raymond lift trucks in one warehouse were selected (pics below, resp.).



Recalling our Operations Research 101 course, we borrow two Economic Replacement sample idea graphs from Unicarriers America Corp. (this is a concept, not a method nor an app!) for Raymond Lifts. With Crown, Raymond is the other major supplier of Forklifts for Cold Storage materials movement:





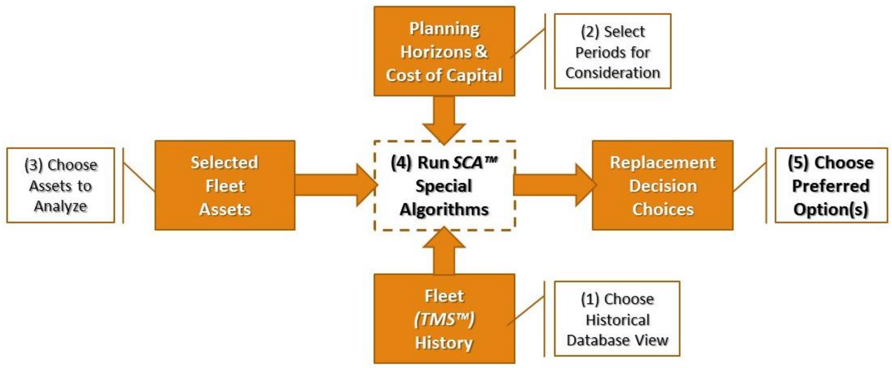
These graphs layout the theoretical picture for Economic Life.

The challenge is to discover the curves of these two graphs in some detail.

The process described below is our attempt at meeting that challenge

Capital Allocation Process: Fleet Economic Replacement (CAP:FER)

We have developed a process with a special algorithm based on dynamic programming to offer CFOs a repeatable process to decide when to replace a specific Asset, in this case, Crown RD lift trucks.



Capital Allocation Process: Fleet Economic Replacement (CAP:FER)

The steps:

1. Choose Historical Database View
   Work Order History provide the necessary information to determine cost of maintenance over time. The cost of parts and cost of labor that go into every visit to the shop matched with the age of the truck and total hours on the meter provide the essential ingredients to estimate cost progression over years and usage. The table below summarizes estimates of ownership cost of a generic truck that cost $30000 and used approximately 800 hours per year. One should note that there are differences between makers and models as far as costs are concerned. Operating environment can also be a factor as some environments might be more corrosive than others resulting in more frequent and expensive maintenance.

Age	Value loss	res_value	maint_cost	Ownership Cost	total_cost
1	0.3	21000	360	1800	2160.0
2	0.46	16200	720	1260	1980.0
3	0.58	12600	1080	972	2052.0
4	0.66	10200	1440	756	2196.0
5	0.71	8700	1800	612	2412.0
6	0.75	7500	2160	522	2682.0
7	0.775	6750	2520	450	2970.0
8	0.8	6000	2880	405	3285.0
9	0.815	5550	3240	360	3600.0
10	0.83	5100	3600	333	3933.0
11	0.84	4800	3960	306	4266.0
12	0.845	4650	4320	288	4608.0

13	0.85	4500	4680	279	4959.0
14	0.85	4500	5040	270	5310.0
15	0.855	4350	5400	270	5670.0
16	0.86	4200	5760	261	6021.0
17	0.874	3780	6120	252	6372.0
18	0.878	3660	6480	226.8	6706.8
19	0.881	3570	6840	219.6	7059.6
20	0.885	3450	7200	214.2	7414.2

2. Select Periods for Consideration
   Analysis reveals that many trucks are used far beyond their economic life. Trucks operating over 15 years are not a rare phenomena. So in essences a complete available history can be beneficial in calculating total cost of ownership over the life of the truck. However, one should be cognizant of price changes over time of parts, labor and the cost of new equipment and make these adjustments forward.

Age (I)	Maint Cost (Cj)	Cumulative Cost	Salvage Value (Sj)	Dep (10%)
1	522.00	522.00	27000.00	3000.00
2	1004.40	1526.40	24000.00	2400.00
3	1447.20	2973.60	21600.00	2160.00
4	1850.40	4824.00	19440.00	1944.00
5	2214.00	7038.00	17496.00	1749.60
6	2538.00	9576.00	15746.40	1574.64
7	2822.40	12398.40	14171.76	1417.18
8	3067.20	15465.60	12754.58	1275.46
9	3272.40	18738.00	11479.13	1147.91
10	3438.00	22176.00	10331.21	1033.12
11	3564.00	25740.00	9298.09	929.81
12	3650.40	29390.40	8368.28	836.83
13	3697.20	33087.60	7531.45	753.15
14	3704.40	36792.00	6778.31	677.83
15	3672.00	40464.00	6100.48	610.05
16	3600.00	44064.00	5490.43	549.04
17	3488.40	47552.40	4941.39	494.14
18	3337.20	50889.60	4447.25	444.72
19	3146.40	54036.00	4002.52	400.25
20	2916.00	56952.00	3602.27	360.23

3. Choose Assets to Analyze

   Projection of costs are made using regression analysis estimate applied on selected truck population (make/model). There are many options of selecting the independent factors, those that we use to explain cost, and the method by which to calculate the regression, depending in the nature of data provided. The results below convey the relationships derived between cost and number of hours used. The equation obtained enables projecting the maintenance cost of the individual truck provided the number of hours used and the projected annual use.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               wins_THC   R-squared:                       0.683
Model:                            OLS   Adj. R-squared:                  0.654
Method:                 Least Squares   F-statistic:                     23.73
Date:                Thu, 16 Jun 2016   Prob (F-statistic):           0.000494
Time:                        11:28:39   Log-Likelihood:                -16.642
No. Observations:                  13   AIC:                             37.28
Df Residuals:                      11   BIC:                             38.41
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const          0.9901      0.557      1.778      0.103        -0.235     2.215
AGE            0.3417      0.070      4.871      0.000         0.187     0.496
==============================================================================
Omnibus:                        0.355   Durbin-Watson:                   1.423
Prob(Omnibus):                  0.838   Jarque-Bera (JB):                0.469
Skew:                          -0.076   Prob(JB):                        0.791
Kurtosis:                       2.082   Cond. No.                         17.0
==============================================================================
```

4. Run SCA™ Special Dynamic Programming Algorithm

   The way we make decisions whether to keep or replace a truck is by looking at the total ownership cost over a planning horizon. To pick the best option of keep and replace over this period one need to calculate all the possible combination of such action from keep the entire period and sell at the end of it or replace every year. This creates a tree of options with total 2 to the power of N where N is the number of years in the planning period. The Dynamic Programming Algorithm truncates the process by allowing progress only on branches that promise leading to the optimum.

   Executing the algorithm for a single truck at a given age and level of usage will provide a plan for this truck as of how long to keep it and when to replace with another truck with similar characteristic.

5. Choose Preferred Options
   The Resulting Decision Table with proposed actions for an individual truck.

	ACOST	ACTION	AGE	KCOST	RCOST	STAGE	T_OPT	CUMM_COST
0	1725.561	K	13	57411.06	57411.06	1	57411.06	1725.560892
1	23219.36	R	14	55948.1	55685.5	2	55685.5	24944.91853
0	0	K	1	32466.15	38115.58	3	32466.15	24944.91853
1	143.7967	K	2	32466.15	40552.62	4	32466.15	25088.71527
2	287.5935	K	3	32322.35	42008.45	5	32322.35	25376.30875
3	431.3902	K	4	32034.76	42483.07	6	32034.76	25807.69897
4	575.187	K	5	31603.37	42351.5	7	31603.37	26382.88594
5	718.9837	K	6	31028.18	41863.72	8	31028.18	27101.86964
6	862.7804	K	7	30309.19	41144.73	9	30309.19	27964.65009
7	1006.577	K	8	29446.41	40194.54	10	29446.41	28971.22727
8	1150.374	K	9	28439.84	38888.15	11	28439.84	30121.6012
9	1294.171	K	10	27289.46	36975.56	12	27289.46	31415.77187
10	1437.967	K	11	25995.29	34081.76	13	25995.29	32853.73928
11	1581.764	K	12	24557.33	30206.76	14	24557.33	34435.50343
12	22975.56	R	13	0	22975.56	15	22975.56	57411.06433

6. Capital plan for the warehouse
   Capital plan involves decisions concerning the entire fleet in the warehouse. Summary of action for the following year will be derived from action plans for the individual trucks in the warehouse.

Warehouse Capital Action Summary

	Action	Age	Asset ID	Hours	Maker	Model	Warehouse	Annual Cost
0	K	9	11836	2313	YALE	ERC050JAN36SEO83	31	127.72
1	R	13	11860	10413	CROWN	30SCTT	31	23142.10
2	K	13	11866	5676	YALE	GPO60TFNUAE085	31	532.47
3	K	12	11876	8207	RAYMOND	OPC30TT	31	1205.98
4	R	12	11877	9830	RAYMOND	OPC30TT	31	22980.13
5	K	12	11878	823	RAYMOND	OPC30TT	31	12.13
6	K	12	11879	2088	RAYMOND	OPC30TT	31	78.06
7	K	12	11880	1385	RAYMOND	OPC30TT	31	34.35
8	R	12	11881	9946	RAYMOND	OPC30TT	31	23021.21
9	K	12	11882	8295	RAYMOND	OPC30TT	31	1231.99
10	R	12	11883	8757	RAYMOND	OPC30TT	31	22623.04
11	R	12	11884	9737	RAYMOND	OPC30TT	31	22947.55
12	K	12	11885	9145	RAYMOND	OPC30TT	31	1497.41
13	K	12	11886	8605	RAYMOND	OPC30TT	31	1325.79
14	K	12	11887	267	RAYMOND	OPC30TT	31	1.28
15	R	12	11888	9447	RAYMOND	OPC30TT	31	22847.94
16	K	12	11889	292	RAYMOND	OPC30TT	31	1.53
17	R	12	11890	9021	RAYMOND	OPC30TT	31	22707.08
18	R	12	11891	9571	RAYMOND	OPC30TT	31	22890.16
19	K	12	11892	1769	RAYMOND	OPC30TT	31	56.03
20	K	12	11893	749	RAYMOND	OPC30TT	31	10.04
21	R	12	11894	9516	RAYMOND	OPC30TT	31	22871.37
22	K	12	11895	8334	RAYMOND	OPC30TT	31	1243.60
23	K	12	11897	7732	RAYMOND	OPC30TT	31	1070.43
24	R	12	11898	9242	RAYMOND	OPC30TT	31	22779.34
25	R	12	11899	9166	RAYMOND	OPC30TT	31	22754.29
26	R	12	11900	9858	RAYMOND	OPC30TT	31	22990.00
27	R	12	11901	9766	RAYMOND	OPC30TT	31	22957.68
28	R	12	11902	9247	RAYMOND	OPC30TT	31	22781.00

This can be the basis of multi-year capital plan. Provided annual budget constraints allowing management to phase out gradually old equipment to ease the budgetary burden of en-mass equipment replacement.

Summary Discussion

The challenge is met!

From 20 years of existing maintenance data and a depreciation schedule, we have created a set of recommended lift truck replacements.

What is interesting is that many of these assets are kept and operated for 20 years and the suggested economic replacement is much less than that. The big “Aha!”: the fleet is very suboptimal in its return on investment. And we now know how to rectify this situation.

The example here produces a table of suggestions for the next year. This table supports a CFO in making an efficient multi-year replacement plan depending on her/his capital budget plan.

The entire process takes less than an hour. Thus, in a day, the CFO can test several scenarios if s/he so desires. This means not necessarily making the decision faster, but that a much better decision can be made with greater confidence.

This is just a first step in applying more better data and exploiting predictive analytics.

As the assets are instrumented with sensors and a gathering and processing infrastructure is in place, maintenance of these assets can be made more efficient thus improving daily operational effectiveness. This is achieved through failure avoidance and fewer trips to the shop.

This is the business case for predictive analytics in the cold storage supply chain.

Next step is predictive maintenance which promises significant annual savings in the maintenance shop operations as well as warehouse floor operational efficacy.

Five-Year Outlook for Predictive Maintenance in the Cold Storage Supply Chain

We visualize a roadmap for the IIoT adoption.

2017: Phase 1: Consolidation of Parts Distribution System—Efficiencies of Channel Compression

Manufacturers continue to develop company parts stores by buying independent distributors as they had been abandoned 20 years ago.

This is met by an opportunity for consolidation into OEM-agnostic parts and maintenance services as well.

There will be no going back this time because e-commerce structures are so efficient.

Boutique 3PL Services will evolve into SaaS offerings.

2018: Phase 2: Consolidation of Parts Distribution System—Expansion of Near-Time Decision Making

As Parts Distribution System consolidates and more sensors are added to assets, opportunities for smaller decision windows abound.

This is primarily due to larger economies of scale to deliver have higher and more precise significance of information. This is value leverage.

Due to the Cloud orientation, the bar is lowered for leveraging predictive analytics like failure forecasting and prevention.

Services for small and medium businesses as well as large ones will emerge and build a more robust ecosystem.

2019: Phase 1: Radical Cost Reduction of Failure Events—Multi-Part Failure Avoidance

The cost of forklift failure and maintenance events is heavily weighted towards labor time versus parts.

Our research shows that each event involves an estimated average of 3.3 mechanic hours plus 1 driver hour per event and $48 in parts. One avoided event is worth $800 Million annually for the forklift maintenance industry.

As the historical operational databases grow, just-in-time repair of forklifts services will emerge. Our research shows that we can today predict additional failures of specific parts within the next week after a single part failure event experience.

Thus, repairing those soon-to-fail parts will avoid the disruption of their failure on materials/goods/produce movement, as well as, more visits to the shop. Weekly and daily scheduling of repair activity will be greatly enhanced. Labor becomes much, much more productive!!

2020: Phase 3: Consolidation of Parts Distribution System—Emergence of Real-Time Command and Control

By this time, the IoT adoption has risen out of the Valley of Disillusionment and crossed The Chasm of Adoption towards rapidly increasing use.

Tracking asset movements is now a reality. Air Traffic Control-like control centers will have multiple dashboards on all aspects of movement. Two-way communication from control center to asset is a reality.

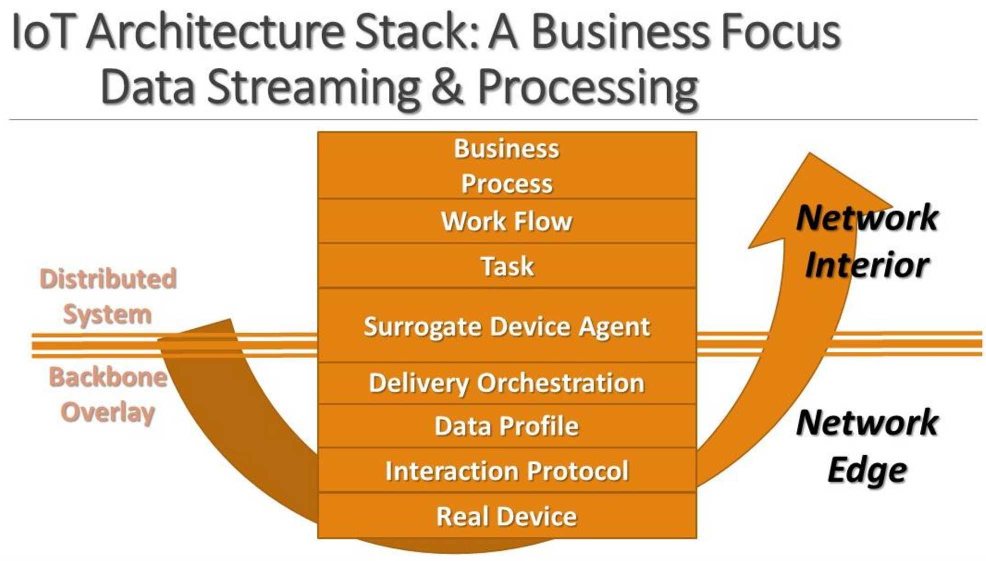
Self-driving forklifts augment automated conveyor systems for the last 100 meters of materials/goods/produce movement.

2021: Phase 1: Radical Cost Reduction of Failure Events—Optimization of Workload Management

The Future of Movement Optimization can now be realized.

Intelligent surrogate agents interact with control processes rendering the reality of Real Time Command and Control of Logistics at an end-to-end macro level all the way down to the micro (roadways) and nano (warehouse floors) levels in the Supply Chain.

Appendix



The IoT Stack, Bottom Up

[Warning this is a bit technical. Skim over this and the next section lightly on first reading.]

As said above, this IoT Stack is a depiction of the infrastructure moving information, data and events, up into the application areas. It is all moving to Assembly, not de novo Construction) of specific Business Capabilities that create Significant Results

The Commodity Layers

There are many objects and processes that are so ubiquitously implemented and available that dealing in them requires large scale to be competitive. These are IT Commodities.

Industrial Assets often are or almost are Commodities. Sustainable Premium value is derived from superior performance against competitive products.

Any Premium IoT benefit derived from these Industrial Assets must be extracted much further up the stack unless a manufacturer can capture and retain their customers within a walled garden.

Device

Devices come in all shapes and sizes with many purposes and capabilities. They are the Things of the Internet. They have names and descriptions which, when defined precisely, define a subset of the Internet that can be operated securely and efficiently.

Sensors are one major Kingdom. And, ***groBotic***™ Intelligent Agents are another. Canonical Objects, these ***groBots***™. There is a dire need for these objects as their reference behavior.

The only real specification of something is a concrete object with desired modifications. Canonical Objects work The Way it is Supposed to Be. They begin the process of improvement.

Interaction Protocol

Interaction Protocols are the way devices “talk” to the world. They have several modalities of operation:

- **MQTT** for machine-to-machine communication (M2M)
- **XMPP** and **WebRTC** for peer-to-peer communication (P2P)
- **JMS**, **MQ**, and **AMQP** for human-to-machine communication (P2M)
- **BYOP™** (Bring Your Own Protocol) for other unique forms of communication

Data Profile

List of data attributes, their structure (see p. 9 above) and formatting. In tech terms, SQL-like.

E.g., a Forklift Data Profile--In each data payload, there would be attribute values totaling 40 bytes:

- Identifier
  ipv6 address: 16 bytes (10^{38}—100 Trillion, Trillion, Trillion different values)
- Location
  GPS coordinates, 2 signed floating point: 8 bytes
- Temperature
  In Kelvin, 1 floating point: 4 bytes
- Vibration
  Cycles per second, integer: 4 bytes
- Fuel Level
  Type, Level; Voltage/Petrol/Natural Gas (1 byte), value in appropriate units (3 bytes): 4 bytes
- Fork Position
  Percentage from the bottom to the top position, floating point: 4 bytes

Delivery Orchestration

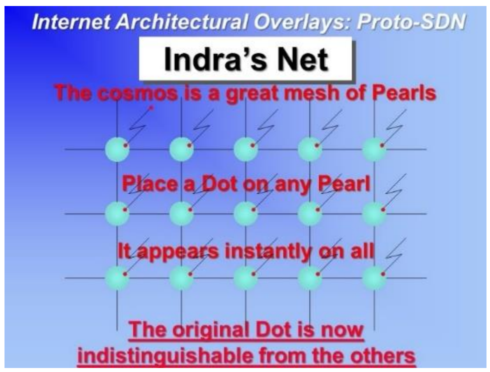
Delivery Orchestration is Process Automation of Data Payload handling. It is done at the Network Edge and next to the EBbO of the Network Mesh (next section).

Each Data Payload is a Postcard from the Edge or a response from the Interior. Sharing of State is achieved through Broadcast/Point-Point/Pub-Sub Messaging or through Data Streaming Channels.

The Network Mesh Connection (Enterprise Backbone Overlay—EBbO.

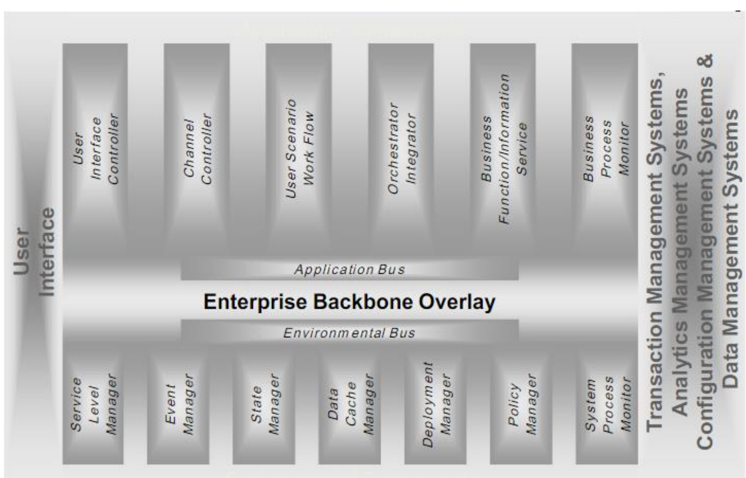
For the past 30 years, we have been moving towards People-Machine, Peer-Peer, Machine-Machine Communication Middleware and Nodal Connections.

In 1995, one author introduced this mesh concept to a conference on scaling systems. The fundamental idea was an Indian God's construction of the Universe. That is, a virtual functional uniformity across a flat mesh network:



Architectural Overlays of the Internet: Proto- Software Defined Networks.

By 2005, he had defined a Standard Infrastructure Architecture with complete functional categories:



And as of today, we are drilling down to the detailed IoT infrastructure functional overlay realization (cf. the Intelligent Agent Manifesto):

- Distributed Yellow Pages
  - Autonomous control among interacting entities
- Listening (Hailing) Port
  - <ipV6>:<num>, default 8080
  - Bot Whistles
    - DES3 Connect Keys
    - Shannon Twin Protocol
- Responding Port
  - <ipV6>:<num>, default 443
- interface (file like)
  - Init(<obj>): reset to Default
  - Splus(<obj>): next value from the <obj>
- Electronic & Mechanical Devices
  - On Board Diagnostics
- Performance Profile (Data Point Sources)
  - Usage Meter
  - Voltage
  - Temperature
  - Vibration
  - Location
    - GPS Coordinates
    - Local Coordinates
  - Spare 2

A Virtual Master Controller Profile
for Forklift IoT within a Software Defined Secure Content Aware Network

There are several Locales where control can be exerted. This diagram lays them out:

Big Data Streaming and Processing Controls

Surrogate Device Agent

This is the layer of Persistence and Driver Objects for all Devices, where all the Intelligent Agents of the Network reside.

These Surrogate Agents live within the Backbone Overlay preserving state and serving processes on either the Edge or in the Interior of the Network.

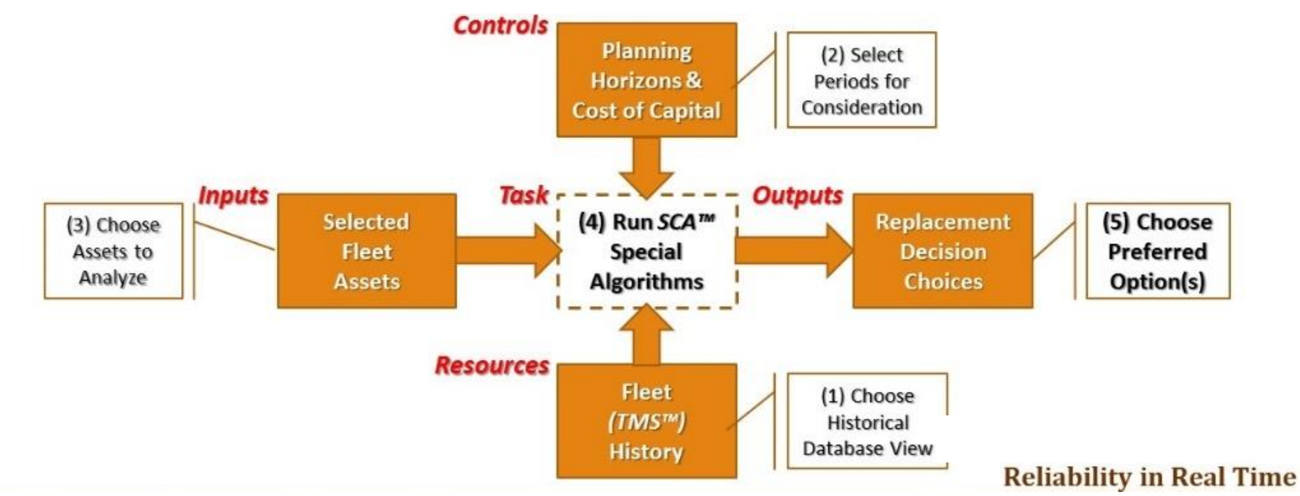
Surrogate Device Agents can be Commodity or Premium objects.

The Premium Layers

Premium objects and processes are how Enterprises build distinctions worthy of special valuation above competitors. They are concentrated in these layers.

Commodity objects and processes exist in the Premium Layers as well. Unique combinations of Commodities can produce very Premium results.

Premium areas are best illustrated by an Exemplary Business Process.



Determining Capital Requirements from Turnover of Fleet Assets

Implementing the above business architecture is covered by the next three sections, Task, Work Flow and Business Process.

Task

Tasks are the individual work steps needed to achieve the eventual result desired. Tasks have different roles in the Workflow as indicated by the diagram above. They can be almost instantaneous or be long-lived over multiple sessions.

SCA™ Special Algorithm Execution is the penultimate step in producing the information necessary for deciding what Assets to keep and which to replace. Load the Metrics, List Recommended Actions, and Decide.

Workflow

Workflow is the sequencing of Tasks to get to a business end-result.

This example here is realization of the SCA™ Capital Allocation: Fleet Economic Replacement Decision. It is triggered by Capital Budget Planning and can be scheduled to run in the background at prescribed intervals or by event.

Business Process

Treasury Operations: Balance Sheet Management

For the Management Processes, metrics are developed, informing and precipitating actions from the Workflows. In the example, An 18-24 Month Fleet Capital Allocation Budget can be based.

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