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A Framework to Measure the Value of IoT in Spare Parts Logistics Networks

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A Framework to Measure the Value of IoT in Spare Parts Logistics Networks

by

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Abstract

A Framework to Measure the Value of IoT in Spare Parts Logistics Networks

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With increasing connectivity and declining data processing costs day-by-day, industrial systems hold a promising future in the wake of technologies like Internet of Things (IoT). Spare-parts logistics networks can leverage continuous sensor data from machines to provide better service to their customers. This work introduces a framework to evaluate the impact of Internet of Things on a multi-echelon spare parts logistics network. A discrete event simulation of a stylized system is developed and numerical experiments are used to study the system-wide effects of different factors like inspection interval and replacement policy. The simulations are used to evaluate the costs under different key factor settings and decision plots are derived to identify the cost settings under which the IoT is beneficial. The results suggest that continuous data collection about the part health can enable early replacement policies which result in reduced total cost. The study also found that in the systems with high holding cost, making inventory and replacement policy decisions jointly can be more beneficial.

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Chapter 1: Motivation

1.1 The Internet of Things:

Internet of Things (IoT) is a system of connected devices that can communicate with each other through the Internet. After the advent of internet, the way we communicate has changed by a great extent. The number of connected devices is increasing at a rapid pace. The IoT connects real world objects and creates an opportunity to impart intelligence to the system to process the information and make useful decisions [1].

According to Gartner, there are 4.9 billion connected things worldwide and predicted that this number would reach 20.8 billion by 2020 [2]. Research firm Internet Data Corporation, in its 2014 report stated that the IoT enabled smart manufacturing can deliver an additional USD 371 billion in revenue in the next four years [3]. McKinsey Global Institute's report on IoT predicted that IoT enabled manufacturing can have a potential impact of USD 1.3-3.7 Trillion per year by 2025 [4]. The report also highlighted that less than 1% of data is being currently used for alarms and real-time control and more can be used for optimization and prediction. Information Technology & Innovation Foundation, in its 2016 update on the state of IoT [5] remarked that the costs of some sensing technologies reduced by 100x in the last decade.

With so many potential gains in revenue and efficiency, the industry has already started investing in building the framework and infrastructure of IoT into their manufacturing processes and products.

1.2 Machine Maintenance Systems:

The performance of every machine deteriorates over time subject to stress and wear. Maintenance should be exercised to maintain performance and production. Maintenance policies can be broadly categorized into three categories namely Corrective Maintenance (CM), Condition Based Maintenance (CBM) and Preventive Maintenance (PM). Corrective maintenance is a practice where the maintenance is triggered by the machine failure. This is also known as Reactive Maintenance. CM generally results in lesser reliability and increased system down-time. PM on the other hand is a practice where maintenance is conducted at regular intervals irrespective of the condition of the machine. PM gives higher reliability but also results in increased maintenance costs. Condition based maintenance emerged as a practice that can take the good of both PM and CM. In CBM, maintenance is conducted based on the health condition of the machine. For CBM to be applied, there should be infrastructure and practices in place which can help get the machine health information without creating disruptions in machine performance. This information is used to make a decision on whether a machine needs maintenance. CBM has gained interest in the recent years due to improvements in monitoring techniques. IoT can be an enabler to apply CBM at scale for geographically dispersed equipment. This is because the health states of different machines in a network can be communicated to a central maintenance service provider and the provider can make decisions with system-wide data at hand. This application of IoT with CBM will be the focus of this work.

1.3 Spare Parts Logistics Networks:

Spare parts for maintaining mission-critical machines are generally distributed using a multi-echelon supply chain network with central warehouses in the top echelon serving stocking locations in the lower echelons and the stocking locations in turn serving the customers [6]. Each stocking location has some customers assigned such that their demand can be served in a reasonable amount of time so that the customers' experienced downtimes are minimized. Generally, these networks are managed by single entities (maintenance service provider) and they serve their customers subject to service contracts. If a machine is down beyond a certain time due to lack of part availability, this hurts the customers' businesses and hence penalizes the maintenance providers for not honoring the service contract. Knowing the part health beforehand can be a win-win situation for both the customers and maintenance providers because the maintenance provider can decide to replace a part before a failure occurs and this would prevent the downtime. With the integration of IoT and CBM technologies, a centralized and continuous health data collection system can be achieved and this information can be used to optimize both the inventory levels of the parts used in maintenance and the conditions at which parts are replaced. This study focuses on impact of such system on a spare parts logistics network.

1.4 RELATED WORKS IN LITERATURE:

Elwany and Gebraeel [7] applied the remaining useful life distributions obtained from sensor data to make optimal inventory ordering and replacement decisions but the inventory is assumed to be held at customer location. The work considered a single machine system and the inventory policy followed is (S-1, S). Jardine *et al*. [8] proposed an optimal maintenance policy by leveraging the vibration monitoring data of bearings, but the work assumed that inventory is always available. Eunshin *et al*. [9] introduced a dynamic optimization model to make optimal maintenance decisions for a wind turbine subjected to stochastic deterioration. The framework represented each turbine as a separate entity and assumed a long lead time for replacement parts to arrive. Merve and Djurdjanovic [10] considered integrated maintenance scheduling and production planning for a multiple machine flexible manufacturing system. The work used simulation and 'tabu' search methodologies to solve the problem.

While many studies treat demand as given and ignore the maintenance planning, on the other end of spectrum, studies on maintenance policy ignore the inventory constraints. The downside of such studies is that they fail to provide a comprehensive view of the system wide effects. Limited studies [11] exist that jointly consider maintenance and inventory. Chen *et al*. [12] considered a multi-echelon spare part logistic network in a joint maintenance and inventory problem. The work applied simulation modeling to identify the joint optimal maintenance and inventory policy for a system with age based preventive replacement of parts. YeWei Cai [13] proposed a Semi Markov Decision Process to implement condition based predictive maintenance for semi-conductor manufacturing processes. Olde Keizer *et al*. [14] modeled the joint inventory and part replacement decision making problem for a multiple component system as a discrete time Markov Decision Process and employed value iteration technique to solve the problem. However, the study only considered collecting health data in regular intervals but did not address the system under continuous monitoring. Continuous monitoring can be helpful in detecting state changes earlier so can result in reduced down-time.

So far there is very little literature that has dealt with measuring value of IoT in spare parts logistics networks. Most of the literature on IoT discusses general frameworks and infrastructure needed to apply the technology but very few worked on analytical aspects of it. Our goal in this work is to show the value of applying IoT to spare parts logistics network and identify the system settings where IoT is beneficial and where it is not. With the help of simulations, we attempt to show the cost and efficiency impacts of IoT. The objective is to provide a framework that helps decision makers measure the quantitative benefits of investing in IoT technology in an existing spare-parts logistics network. This framework can be of great help for maintenance providers to make strategic decisions on whether to invest in advanced technologies to monitor machine health. It can also be of great help in negotiating service contracts with customers.

The rest of the report is organized as follows: Chapter 2 discusses the system under consideration and the key assumptions made. Chapter 3 describes the order of events and input parameters and output metrics for the discrete event simulation of the system. Chapter 4 discusses the numerical experiments and results. Finally, Chapter 5 presents conclusions and future scope of the work.

Chapter 2: System Setup

2.1 Spare Parts Logistics (SPL) Network

In this work, we focus on studying the impact of IoT on spare parts logistic networks. We consider a multi-echelon spare parts logistics network that consists of a central warehouse (CW), multiple stocking locations (SL) each serving a group of geographically dispersed customers whose machines might need the spare parts in case machines in use fail. The stocking locations are strategically located so that they can serve customers in a reasonable amount of time to minimize the downtime experienced by customers. The stocking locations hold inventory of spare parts required by customers they serve and inventories are replenished by the central warehouse when required. Figure 2.1 shows a representation of a spare parts logistics network.

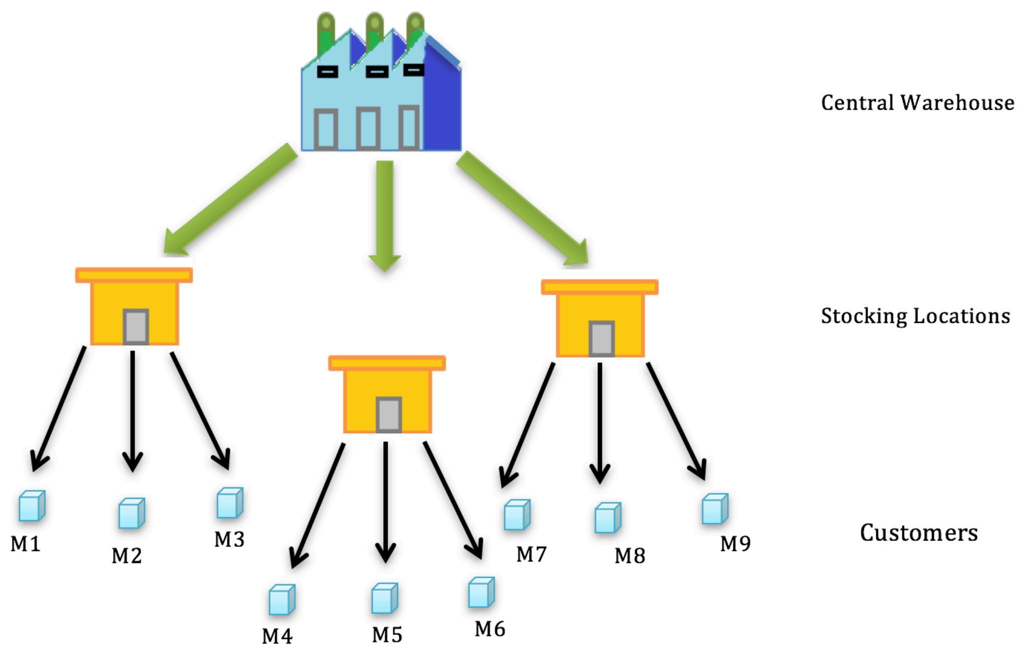

Figure 2.1: Representation of a two-echelon spare-parts logistics network with single warehouse 3 stocking locations, and 9 customers

Here we introduce some terms that we will be using in the rest of the report:

Standard Shipping Time (t_s):

The standard shipping time 't_s' is the time taken for the part to reach the customer when shipped from a stocking location.

Emergency Shipping Time (t_e):

The emergency shipping time 't_e' is the time taken for the part to reach the customer when shipped from the central warehouse. This happens in case of a stock-out at the stocking location trying to serve the customer.

Inventory Replenishment (lead) Time (t_l):

The inventory replenishment time 't_l' is the time to replenish inventory at the stocking locations from the central warehouse, which is assumed not to stock out at all.

Inspection Interval (t_i):

The inspection interval 't_i' is the time between two consecutive health/condition inspections of a machine at a customer's site.

Replacement Policy (p_r):

The replacement policy 'p_r' is the machine state at which a replacement part is requested from the stocking location to the customer's location.

2.2 IoT in SPL Network

As introduced in the previous chapter, this study focuses on identifying the right scenarios where applying IoT to an SPL network can be beneficial. In an SPL network with CBM and no IoT applied, the machines are inspected at regular intervals manually and the health information is communicated to the stocking locations which make a decision whether or not to send a new part to the customer. When IoT is applied, the health information of the machines at customer locations can be sent to their assigned stocking locations without the need of a manual inspection.

This key differentiation is what we will base on when we make an attempt to compare the costs of 'IoT' and 'no-IoT' scenarios in this work.

2.3 Assumptions:

The following are the key assumptions we make for the system:

1. There is one central warehouse with unlimited inventory of parts.
2. One machine of a single type is at use in each customer location.
3. The machine has only one critical part which determines its health.
4. The condition of the part is discretized to a finite number of states where:
    a. 0 corresponds to the as-good-as new condition
    b. The largest possible state corresponds to the failed condition
5. From installation to failure the part health follows a Discrete Time Markov Process.
6. Each stocking location uses an (s, S) policy to manage and replenish the inventory of the spare parts.
7. The replenishment lead times (between the central warehouse and the stocking locations) are known and constant.
8. Once the spare reaches the customer, the replacement of an old part with the new spare is instantaneous.
9. The machine health state is communicated to the stocking location at each inspection (controlled by the inspection interval).
10. Part failures are communicated to the stocking location immediately.
11. Condition-based replacement policy determines the condition in which a part replacement is triggered.

In the next chapter, we describe the system simulation built considering all the assumptions stated in this chapter.

Chapter 3: System Simulation

3.1 Discrete Event Simulation

To model the behavior of the two-echelon spare parts logistics system described in the previous chapter, a discrete event simulation model is built using Python programming language. The simulation progresses in discrete time units of one day. A key advantage the simulation study provides is that we can study behavior of a complex system for different policy changes. In the current version, the simulation model is built to run for a system with a single central warehouse, single stocking location, and up to two customers, each with one machine in continuous use.

3.2 Simulation Inputs

Table 3.1 details the input parameters to the simulation.

#	Name	Description
1	Length (l)	The number of time units starting from zero for which the simulation is run
2	Number of customers	The number of customers (equal to the number of machines)
3	Transition probability matrices	For each machine present in the system, the probability transition matrix gives the probability mass of the next state, given the current state
4	Replacement policies	For each machine at the customer location, the machine state at which the customer requests a new replacement part from the stocking location (or the central warehouse depending on part availability)
5	Fail states	The indices of failure states for each machine in the system. This is generally the final state of the transition probability matrix
6	Standard shipping times	For each customer, the standard shipping time to ship a part from the stocking location to the customer
7	Emergency shipping times	For each customer, the time to ship a part from the central warehouse. This option is exercised only when the stocking facility has no on-hand inventory and demand from the customer arises
8	Maximum inventory level	Order-up-to level S for the stocking location and the inventory on hand at the beginning of the simulation
9	Minimum inventory level	Reorder point s for the stocking location
10	Inventory replenishment time	The lead time for the inventory to be replenished at the stocking location from the central warehouse
11	Inspection interval	This indicates how often the stocking location wants to know the states of different machines that it is serving

Table 3.1: Simulation inputs

3.3 Order Of Events

Here we try to capture a screenshot of simulation at a given moment to to explain the overall process and order of events. Let us consider a sample scenario with one customer, one stocking location and one warehouse and with inspection interval set to one. At the end of day 't-1' let us assume that there are 'I' units of inventory at the stocking location and the machine at the customer location is in state 'j_1'. At the beginning of day 't' suppose machine has transitioned to a state 'j_2' ($j_2 \geq j_1$). If the new state 'j_2' is a "replacement state", i.e., $j_2 = p_r$ then we trigger a demand from the customer to the stocking location. If the stocking location has the inventory, i.e., $I > 0$, then the stocking location will dispatch a new part right away and it will take 't_s' units of time for the part to reach to the customer. Otherwise, if $I = 0$, the demand is passed to the central warehouse and the central warehouse which ships the part as an emergency shipment right away to the customer. In this case, the shipment will take 't_e' amount of time for the part to reach the customer. During shipping (standard or emergency) the machine continues to degrade at the rate described by the transition probability matrix. In the case when $I = s$, an inventory replenishment order (with order size equal to the order up to level S less the reorder point s) is initiated and the central warehouse ships the required quantity of new parts which will arrive after 't_l' amount of time at the stocking location. Once the new replacement spare-part arrives at the customer location, the existing part will be replaced instantaneously with the new part (the machine may be working or in the fail state). After the part replacement, the machine comes back to the good-as-new condition (state 0) and the machine use starts with deterioration as explained earlier.

3.4 Simulation Outputs

Table 3.2 details the output measures collected from the simulation runs. Outputs can be used to measure how the system has performed for a combination of input parameters.

#	Name	Description
1	Sample state paths	For each machine, throughout the length of the simulation we trace the state paths of the machines. For each machine, it will be a vector of length 'l'. The elements of the vector represent state path of the machine.
2	Inventory	The inventory level at the stocking location as a function of time. This will also be a vector of length 'l'.
3	System down-time	Sum of the number of days each machine spent in fail state during the simulation.
4	Standard shipment timestamps	An array of tuples with each tuple containing information on which day and to which customer a part was shipped from the stocking location.
5	Emergency shipment timestamps	An array of tuples with each containing information on which day and to which customer a part was shipped from the central warehouse.
6	Inventory replenishment timestamps	Timestamps indicating times when the stocking location ordered replenishments from the central warehouse.

Table 3.2: Simulation outputs

In the next chapter, we discuss how we leverage the simulation model to study the costs of different combinations of input parameters on the outputs.

Chapter 4: Numerical Experiments and Results

As explained in the previous chapter, the simulation study can be used to study how the system responds to different policy changes such as part replacement decisions and inventory levels, and system parameters such as shipping times and transition probability matrices. With the output metrics generated by the simulation, the overall costs of different policies can be compared by assigning costs to shipping, inventory holding, and downtime. As the system behavior is highly dependent on the transition probability matrix, we study example systems with different underlying transition probability matrices.

For the numerical experiments, we have considered a single central warehouse, single stocking location. For each input factor, multiple levels are chosen and all feasible combinations are experimented. Each simulation run is 365 days long and is repeated 50 times and the results are aggregated over the repetitions. We evaluate the combinations after assigning cost parameters to the outputs and calculating total cost of each combination. Table 4.1 below shows the details about different factor levels we use in this study. Figures 4.1-4.3 show the transition matrices we use in the numerical experiments. The health of the critical part is assumed to have 10 discrete states where 0 corresponds to new and 9 corresponds to failure. The number in the parentheses next to the matrix name is the Mean Time to Failure (MTTF) for a new part whose health condition follows the given matrix.

Factor	Levels Used
Standard Shipping Time (t_s)	1
Emergency Shipping Time (t_e)	1, 5
Inventory Replenishment Time (t_l)	5
Inspection Interval (t_i)	1, 7, 15, 28, 56
Replacement Policy (p_r)	3, 4, 5, 6, 7, 8, 9
Inventory Level Min (s)	1, 2, 3, 4, 5, 6, 7, 8, 9
Inventory Level Max (S)	2, 3, 4, 5, 6, 7, 8, 9, 10
Transition Matrices (P)	P1, P2, P3

Table 4.1: Factor levels used in the numerical experiments

$$P3(21) = \begin{bmatrix} 0.7 & 0.15 & 0.15 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.7 & 0.15 & 0.15 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.7 & 0.15 & 0.15 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.7 & 0.15 & 0.15 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.7 & 0.15 & 0.15 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.7 & 0.15 & 0.15 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.7 & 0.15 & 0.15 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.7 & 0.15 & 0.15 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.7 & 0.30 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{10\times 10}$$

Figure 4.1: Transition probability matrix P3 with MTTF of 21 days

$$P2(31) = \begin{bmatrix} 0.8 & 0.1 & 0.1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.8 & 0.1 & 0.1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.8 & 0.1 & 0.1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.8 & 0.1 & 0.1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.8 & 0.1 & 0.1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.8 & 0.1 & 0.1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.8 & 0.1 & 0.1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.8 & 0.1 & 0.1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.8 & 0.2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{10\times 10}$$

Figure 4.2: Transition probability matrix P2 with MTTF of 31 days

$$P1(62) = \begin{bmatrix} 0.9 & 0.05 & 0.05 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.9 & 0.05 & 0.05 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.9 & 0.05 & 0.05 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.9 & 0.05 & 0.05 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.9 & 0.05 & 0.05 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.9 & 0.05 & 0.05 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.05 & 0.05 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.05 & 0.05 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{10\times 10}$$

Figure 4.3: Transition probability matrix P1 with MTTF of 62 days

We introduce some cost parameters that we will be using in the rest of this chapter to compare different scenarios.

Manual Inspection Cost Rate (r_i):

As introduced in Chapter 2, t_i is the inspection interval which describes how often, the stocking locations get information about the health of machines that they serve. In absence of IoT, the inspection happens manually and the information is sent to the stocking locations. r_i is the cost incurred per manual inspection per machine. So, this applies to 'no-IoT' case.

Data Collection Cost Rate (r_c):

When IoT is applied to a system, the health information that is collected is sent to the stocking locations via the IoT infrastructure. There is a cost associated with collecting the data and processing it. r_c is the cost incurred per data collection per machine. So, this cost applies to the 'IoT' case.

Down-time Penalty Cost Rate (r_d):

Every day a machine is down because of a failed part, the maintenance provider incurs a penalty cost $r_{d.}$

Inventory Holding Cost Factor (r_h):

The annual inventory holding cost is calculated by multiplying the average inventory value with the inventory holding cost factor. The factor has a value between 0 and 1.

Inventory Ordering Cost (c_o):

The inventory ordering cost is the fixed cost incurred for every inventory replenishment order.

New Part Cost (c_N):

Every time a part is replaced with a new one, a cost c_N *is* incurred to the maintenance provider.

Annual Logistics Cost:

The logistics cost is the sum of the shipping costs for the parts, inventory holding costs at the stocking location and the fixed costs for inventory orders.

Annual Operations Cost:

The operations cost is the sum of new parts costs, and logistics costs, and the inspection costs.

Annual Total Cost:

The total cost is the sum of operations cost and down-time penalty cost.

4.1 Example System I:

Here we consider a two-echelon spare parts logistics network with a single central warehouse, single stocking location and two customers.

4.1.1 Evaluating Policies

For every transition probability matrix mentioned above total of 2030 combinations of the factors are experimented. As mentioned before, we assign costs to different outputs from the simulation to calculate the total cost of the combination and use this to evaluate the policies against each other.

Figure 4.4 shows the trends of total cost, operations cost and down-time penalty cost (all costs are annual, averaged over 50 simulation runs) for different inspection intervals and different replacement policies (machine conditions for part replacements) for IoT condition. The factors that are fixed are P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 0.25$. We notice as expected that for all inspection intervals, the operations costs go down with increase in p_r (as the part is replaced less and less frequently increasing the risk of failure) while the down-time penalty costs go up. The total cost which is the sum of operations cost and the down-time penalty cost goes down initially and then starts to increase after a minimum in all the three inspection interval scenarios.

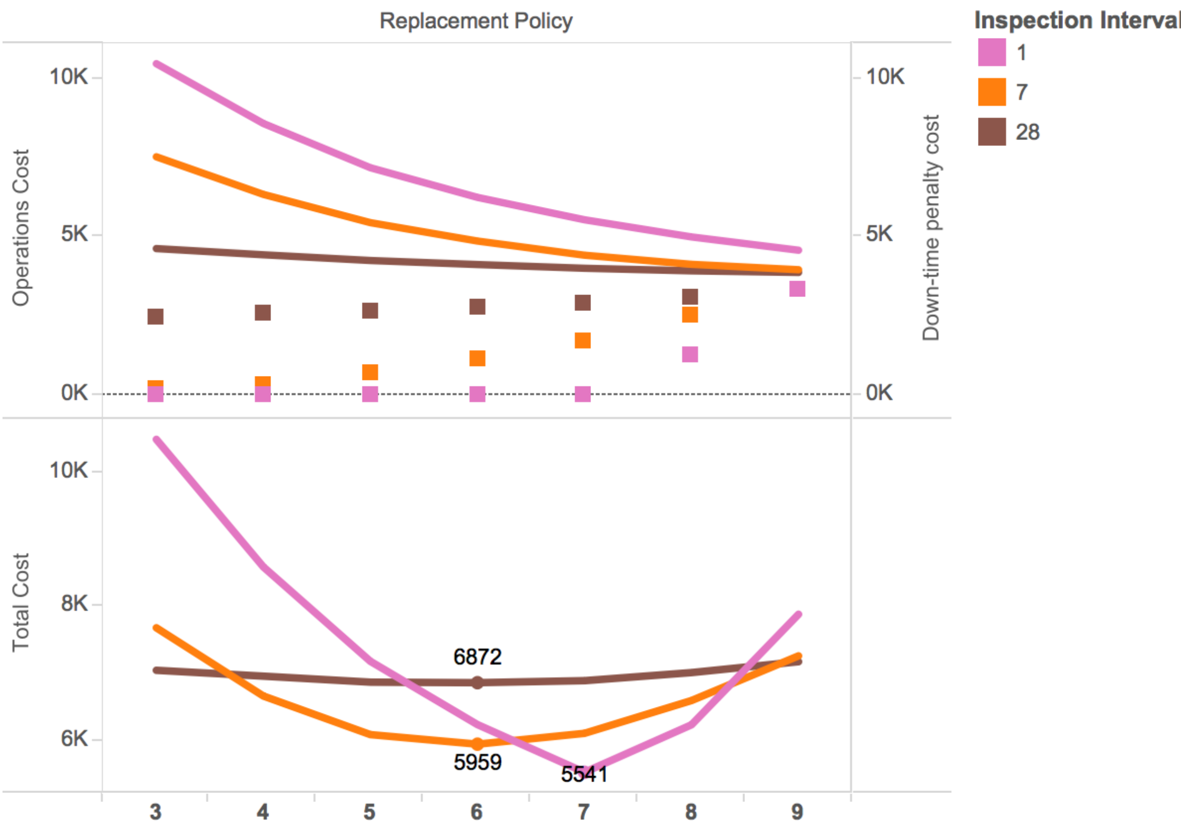

Figure 4.4: The trends of operations cost, down-time penalty cost and total cost for replacement policy. Color shows details about inspection interval. (P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 0.25$)

While the total cost curve for $t_i = 28$ is less sensitive to the replacement policy, the one for t_i=1 is very sensitive. This is because when we have frequent information about machine health, we can identify the transitions to replacement state more frequently and take early actions to send a replacement part. The probability of identifying transitions at the right time reduces with increase in inspection interval. Although shorter inspection intervals increase the operations costs for each replacement policy, the total costs go down due to down-time costs savings that come with more frequent inspections. This leads to a potentially different replacement policy depending on the inspection interval. For example, when the inspection interval is 7 or 28, the best condition to replace the part is 6 as it leads to the lowest total costs and the best condition to replace the part is 7 when the machine condition is inspected every day. Hence, we would choose to replace the part at higher condition and still achieve a lower cost when $t_i = 1$ than in the case of $t_i = 28$. If we change the underlying transition probability matrix and keep everything else the same, we get the results as in Figure 4.5 (P = P2(31)) and Figure 4.6 (P = P1(62)). Note that, inspecting every day (t_i = 1) does not result in the overall minimum total cost in either of these cases.

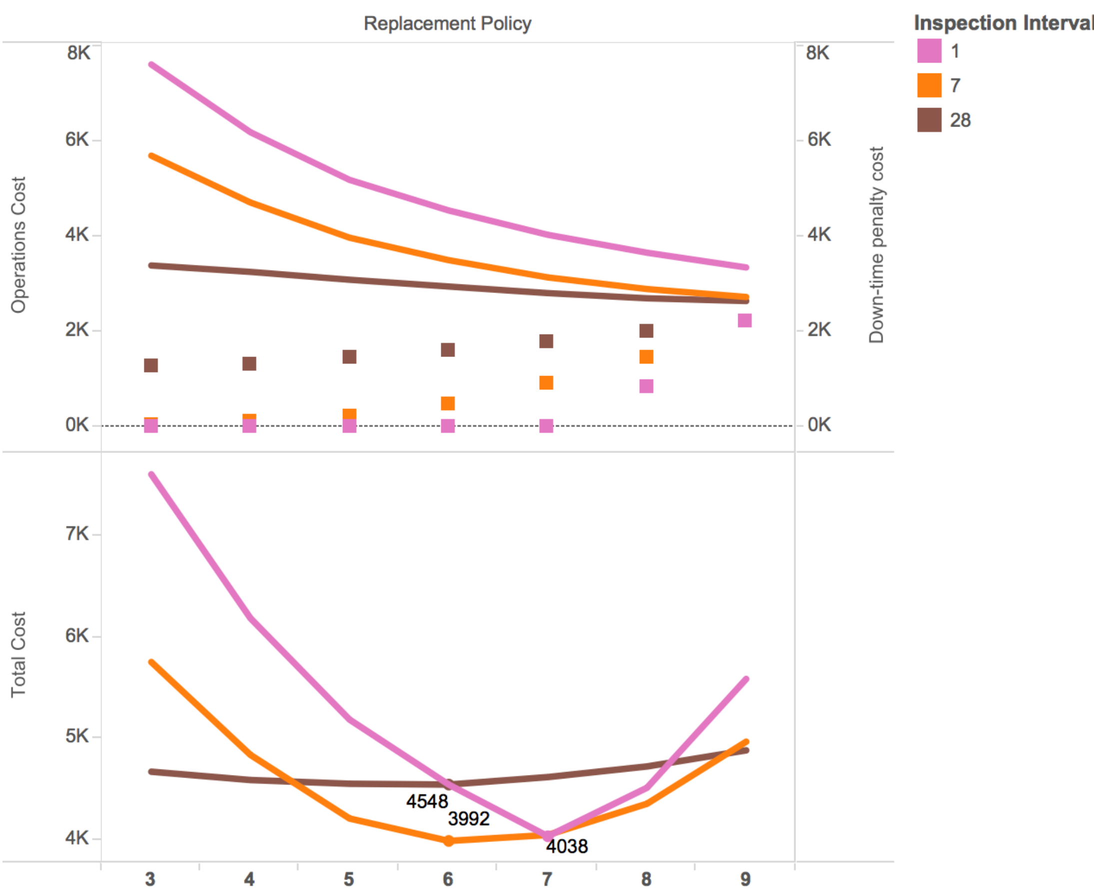

Figure 4.5: The trends of operations cost, down-time penalty cost and total cost for replacement policy. Color shows details about inspection interval. (P = P2(31), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 0.25$)

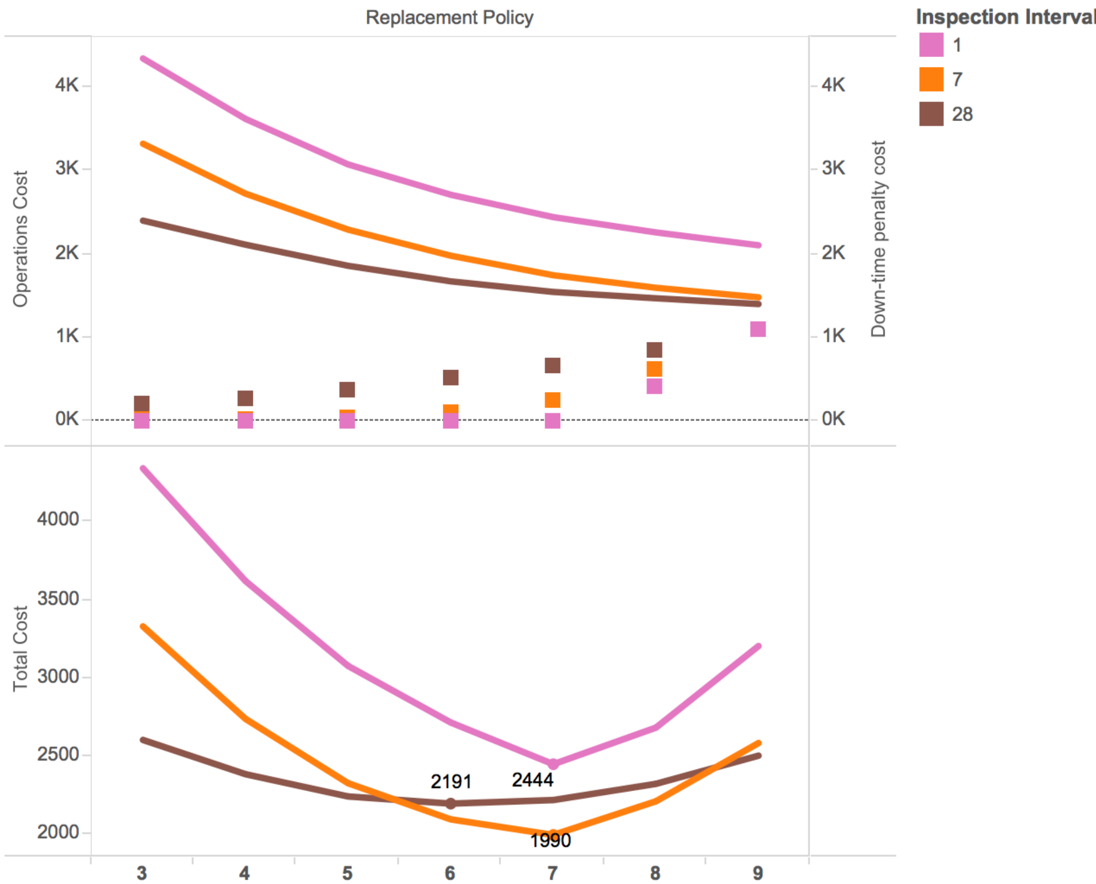

Figure 4.6: The trends of operations cost, down-time penalty cost and total cost for replacement policy. Color shows details about inspection interval. (P = P1(62), $t_e = 1$, $t_s = 1$, t_l = 5, $S = 10$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 0.25$)

This happens because as the system becomes more reliable as in the cases of Figures 4.5 and 4.6, inspecting weekly i.e., $t_i = 7$, may be better overall, as the costs increase due to inspecting more frequently would dominate the savings in the down time penalty costs. However, for systems like the one in Figure 4.5 (P = P3(21)), it may be more beneficial to collect data on a regular basis i.e., $t_i = 1$.

4.1.2 Comparing IoT vs non-IoT Scenarios

In this section, we compare the total cost of IoT scenarios with non-IoT scenarios for some factor settings. Figure 4.7 shows the trends of total cost, operations cost and down-time penalty cost for different replacement policies (all costs are annual) for IoT and non-IoT conditions on the left and right respectively. The factors that are fixed are P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $r_i = 6$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 0.25$. We notice that in non-IoT scenario, the operations cost for the policy with minimal total cost is 5389 units and the down-time penalty cost is 1092 units (corresponding to replacement condition of 6). In the IoT scenario, the operations cost went up to 5541 units but the down-time penalty cost has come down to 0 units for the minimum total cost policy (corresponding to a different replacement condition, 7). Thus, the IoT scenario results in a reduction of the total cost from 6841 to 5541 units. That is a 19% reduction in total costs when compared to the non-IoT best policy. This is one example where applying IoT will be beneficial.

Now let us consider a similar scenario with all factors except r_c are kept at the same values as the previous example. The factors that are fixed are P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 3$, $r_i = 6$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 0.25$. Note that r_c represents the data collection costs for the IoT case and its value is increased to 3 from 1 in the previous example. Figure 4.8 shows the trends of total cost, operations cost and down-time penalty cost for different replacement policies (all costs are annual) for IoT and non-IoT conditions on the left and right, respectively. The non-IoT scenario's costs stay at the same place as the previous example as we have not changed the value of the manual inspection cost rate, r_i. The IoT scenario now results in operations cost of 7001 units and down-time penalty cost of 0 units. The IoT scenario now results in operations cost of 7001 units and down-time penalty cost of 0 units. Thus, IoT scenario results in increase of the total costs from 6481 to 7001 units. That is an 8% increase of cost from the previous best policy. Clearly applying IoT is not very beneficial in this case.

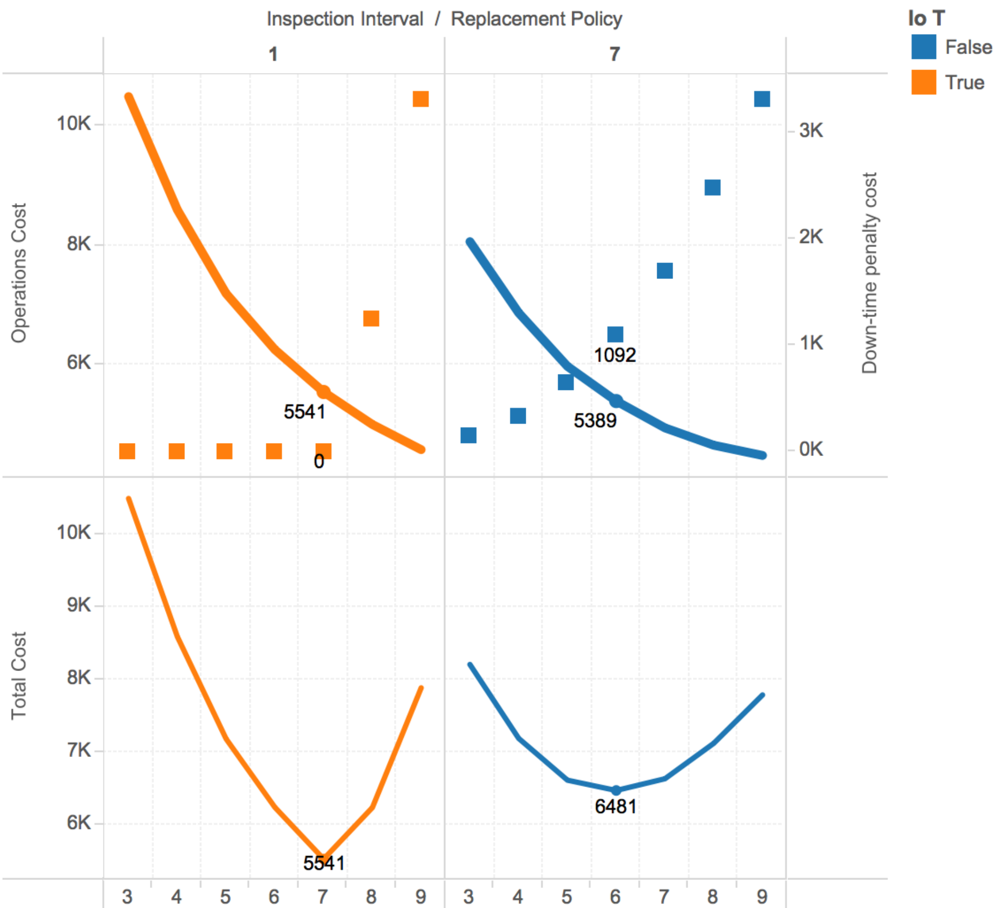

Figure 4.7: The trends of operations cost, down-time penalty cost and total cost for replacement policy broken down by Inspection Interval. Color shows details about IoT. (P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $r_i = 6$ $c_N = 100$, $c_o = 20$, $r_d = 100$, r_h = 0.25)

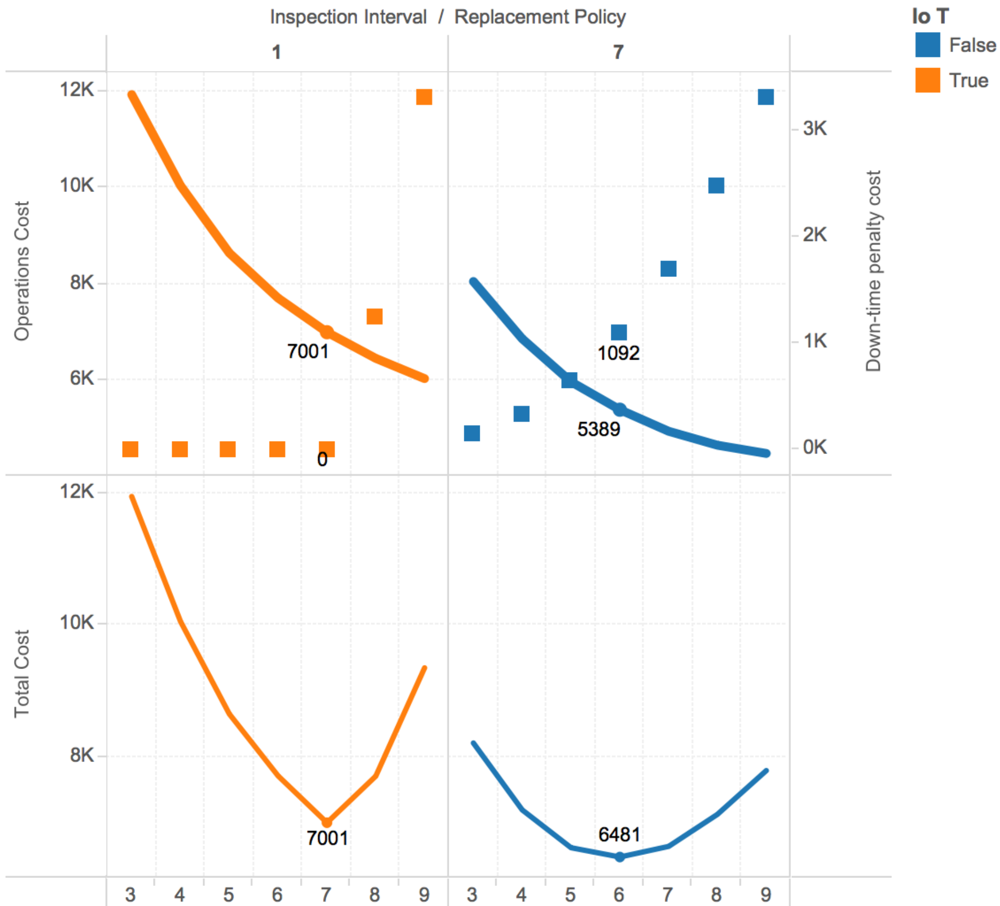

Figure 4.8: The trends of operations cost, down-time penalty cost and total cost for replacement policy broken down by inspection interval. Color shows details about IoT. (P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 3$, $r_i = 6$, $c_N = 100$, $c_o = 20$, $r_d = 100$, r_h = 0.25)

4.1.3 Identifying Key Factors and Deriving Decision Plots

From the results discussed in the previous sections we observe that the key cost factors that affect the IoT decisions are:

- The Probability Transition Matrix (P)
- New Part Price (c_N)
- Down-time Penalty Cost Rate (r_d)
- Manual Inspection Cost Rate (r_i)
- Data Collection Cost Rate (r_c)

By varying the values of these key factors, we can create boundary plots which can help us identify the situations where IoT is beneficial and quantify the value. Here, we will make Decision Plots to help decide between t_i = 1 with IoT and t_i = 7 and no-IoT for different matrices and a range of key cost factors discussed above. Table 4.2 below shows the levels of factors used. For each option, i.e., t_i = 1 with IoT and t_i = 7 with no-IoT, and for a given combination of the factors, we calculate the costs and evaluate the minimum total cost for each option, and calculate the difference in the minima. If the IoT option results in a higher total cost than no-IoT option, then the recommendation is not to go for IoT. If the IoT option results in a lower total cost, then the recommendation is to go for IoT.

Factor	**Levels Used**
New Part Price (c_N)	10, 20, 30, 40, 50, 60, 70, 80, 90, 100
Down-time Penalty Cost Rate (r_d)	10, 20, 30, 40, 50, 60, 70, 80, 90, 100
Manual Inspection Cost Rate (r_i)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Data Collection Cost Rate (r_c)	0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5

Table 4.2: Factor levels used in generating the Decision Plots

For each option mentioned above we evaluate 10,000 combinations of the factors to prepare the Decision Plots. Figure 4.9 shows the Decision Plot for down-time penalty cost rate (r_d) fixed at 10 units and manual inspection cost rate (r_i) fixed at 1 unit for the system with P = P3(21), varying the new part cost and data collection cost rate on x and y axes, respectively. At each intersection of the x and y axes we have a decision, whether to choose IoT. The size of the marker is representative of the absolute difference of the total costs of the IoT case and the no-IoT case, as a percentage of the total cost of the no-IoT case (labeled as 'abs. % premium'). The color of the marker is red if the total cost for the IoT case is more than the total cost for the no-IoT case. The color of the marker is green otherwise (i.e., meaning IoT is more beneficial).

Figure 4.9: New part price vs. data collection cost rate. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. The marks are labeled by % change in total cost. (P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_i = 1$, $r_d = 10$, $c_o = 20$, $r_h = 0.25$)

Figure 4.10: New part price vs. data collection cost rate. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. The marks are labeled by % change in total cost. (P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, S = 10, $s = 1$, $r_i = 1$, $r_d = 100$, $c_o = 20$, $r_h = 0.25$)

We notice from Figure 4.9 that when $r_i = 1$ and $r_d = 10$, IoT case results in higher total costs in all the combinations tested. This is evident from all red markers in the figure. In fact, as the new part price goes down and/or the IoT data collection rates go up, the no IoT with manual inspection every 7 days becomes increasingly better. If we increase the down time penalty, r_d, to 100 from 10 and keep everything else the same, then we get the Decision Plot in Figure 4.10. Here, when $r_i = 1$ and $r_d = 100$, the IoT case can result in lower total costs in some combinations of data collection cost and new part price. These combinations are marked by the green markers in the figure. If the data collection cost rate (r_c) is 0.5 units and the new part price (c_N) is 10 units then applying IoT can bring down the total costs by almost 27%. As the data collection costs increase, we can observe the size of green markers reducing which means that IoT savings come down with increase in data collection costs and after certain point IoT becomes costlier than the no-IoT option. When data collection cost rate is 1.0 units and new part price is 20 units in Figure 4.10, we notice that the IoT results in savings of 6.3% but when data collection cost rate is increased to 1.5 units, IoT option ends up nearly 13.2% costlier. The shift that we observe in Figure 4.10 highly depends on the key factors. For example, if we change the underlying matrix to P2(31) and keep everything same as in Figure 4.10, we get a Decision Plot shown in Figure 4.11. We observe that there are fewer green markers in Figure 4.10 than in Figure 4.9.

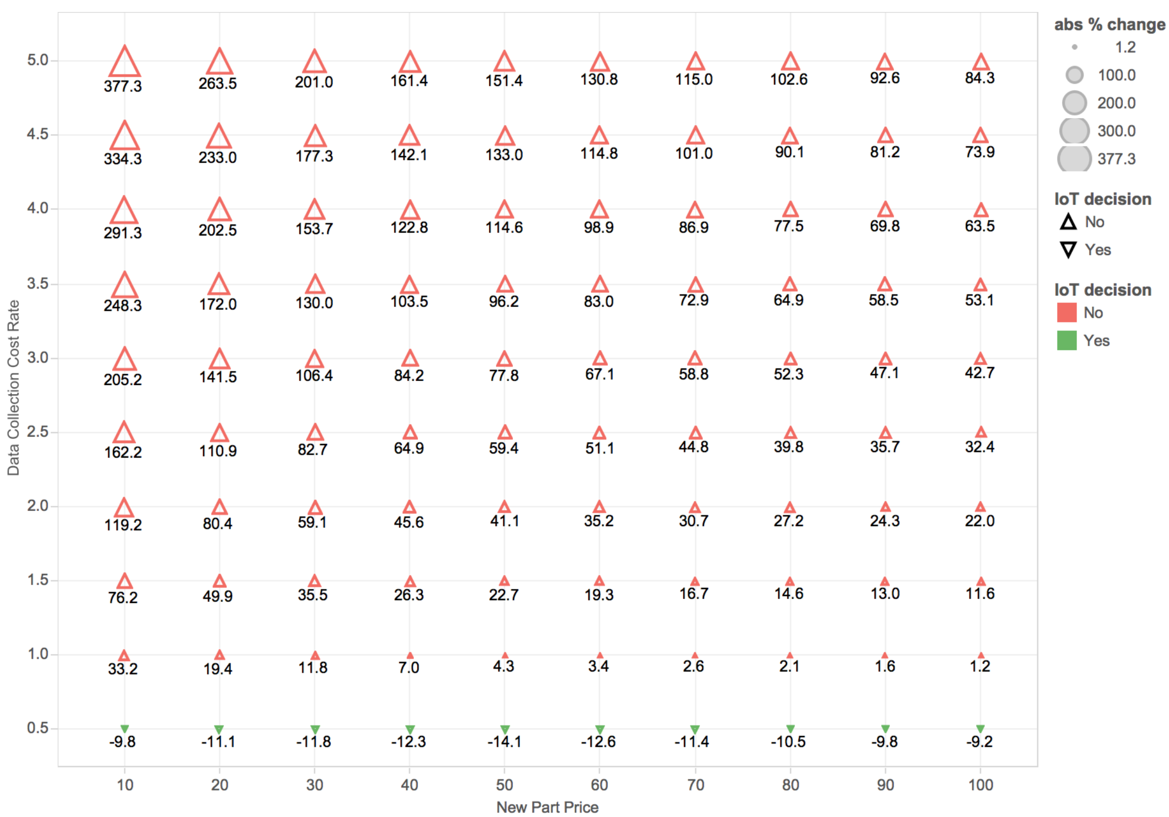

Figure 4.11: New part price vs. data collection cost rate. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. The marks are labeled by % change in total cost. (P = P2(31), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_i = 1$, $r_d = 100$, $c_o = 20$, $r_h = 0.25$)

To understand how the Decision Plots change with changes in the key factors, we generate a side by side comparison of Decision Plots by varying one factor. Figure 4.12 shows the Decision Plots for P = P3(21) where the down-time penalty cost rate increases from left to right. We observe that as the down-time penalty cost rate increases, the number of scenarios where IoT is beneficial also increase. In Figure 4.13 we vary the manual inspection cost rate while keeping all other factors fixed. Figure 4.14 shows Decision Plots for different transition probability matrices. We observe in Figures 4.13 and 4.14, the number of green markers increasing from left to right. From Figure 4.14 we notice that as the system becomes more reliable, the data collection costs need to be much lower for the IoT to be beneficial.

Figure 4.12: New part price vs. data collection cost rate broken down by down-time cost rate. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. (P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_i = 1$, $c_o = 20$, $r_h = 0.25$)

Figure 4.13: New part price vs. data collection cost rate broken down by manual inspection cost rate. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. (P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_d = 100$, $c_o = 20$, $r_h = 0.25$)

Figure 4.14: New part price vs. data collection cost rate broken down by matrix. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. ($t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_d = 100$, $r_i = 10$, $c_o = 20$, $r_h = 0.25$)

4.2 Example System II:

In the previous sub-section, we have studied the systems which deteriorate per the transition probability matrices introduced in Figures 4.1-4.3. While the three matrices result in different MTTF, they have a similar structure. In this sub-section, we study a system with a transition probability matrix of a different structure. Figure 4.15 shows the matrix P4 with MTTF of 28 days. The key difference between P4 and rest of the matrices i.e., P1-P3, is that in case of P4, there is a non-zero probability that a part can fail from any state whereas in P1-P3 the part can fail only in state 7 or 8.

$$P4(28) = \begin{bmatrix} 0.9 & 0.033 & 0.033 & 0 & 0 & 0 & 0 & 0 & 0 & 0.033 \\ 0 & 0.9 & 0.033 & 0.033 & 0 & 0 & 0 & 0 & 0 & 0.033 \\ 0 & 0 & 0.9 & 0.033 & 0.033 & 0 & 0 & 0 & 0 & 0.033 \\ 0 & 0 & 0 & 0.9 & 0.033 & 0.033 & 0 & 0 & 0 & 0.033 \\ 0 & 0 & 0 & 0 & 0.9 & 0.033 & 0.033 & 0 & 0 & 0.033 \\ 0 & 0 & 0 & 0 & 0 & 0.9 & 0.033 & 0.033 & 0 & 0.033 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.033 & 0.033 & 0.033 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.033 & 0.066 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}_{10\times 10}$$

Figure 4.15: Transition probability matrix P4 with MTTF of 28 days

4.2.1 Analyzing Cost Curves

For the matrix P4 introduced above, total of 2030 combinations of the factors are experimented. We use the simulation outputs to calculate the costs of different combinations of parameters.

Figure 4.16 shows the trends of total cost, operations cost and down-time penalty cost for different replacement policies (all costs are annual) for the IoT case. The factors that are fixed are P = P4(28), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $c_N = 100$, $r_d = 100$. We notice that for all inspection intervals, the operations cost goes down with increase in replacement policy while the down-time penalty costs go up (though the increase in down-time penalty cost is not very significant). The total cost for all the inspection intervals go down with increase in replacement policy. This means at this system settings, it is best to wait till the part fails than replacing it any earlier. We notice that unlike in Figure 4.4, there is no interaction between the total cost curves of different inspection intervals. Total cost is always higher for $t_i = 1$ than for $t_i = 7$ and $t_i = 28$.

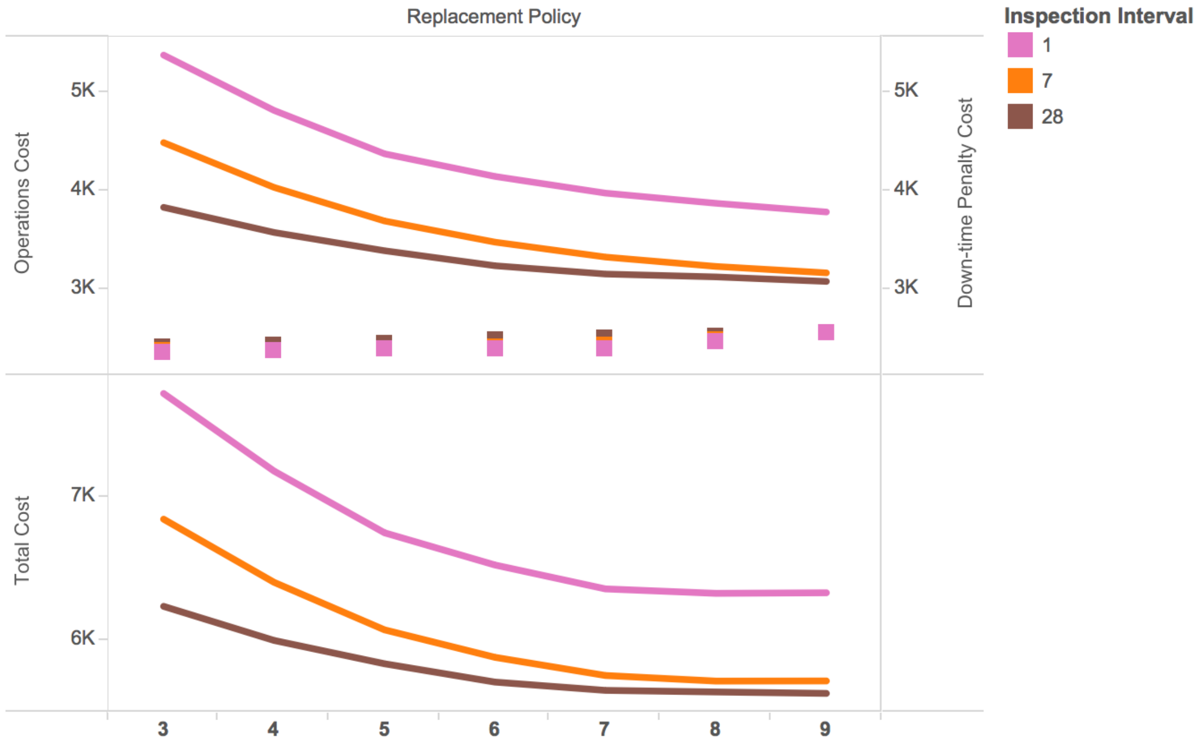

Figure 4.16: The trends of operations cost, down-time penalty cost and total cost for replacement policy. Color shows details about inspection interval. (P = P4(28), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $c_N = 100$, r_d =100, $c_o = 20$, $r_h = 0.25$)

If we increase r_d from 100 to 200 while keeping other parameters same as in Figure 4.16, we get the plot in Figure 4.17. Now we can see that the total cost reaching a minimum at $p_r = 7$. Though the total cost of $t_i = 1$ is always higher than the total cost of $t_i = 7$ and $t_i = 28$, there is some interaction between total cost curves of $t_i = 7$ and $t_i = 28$.

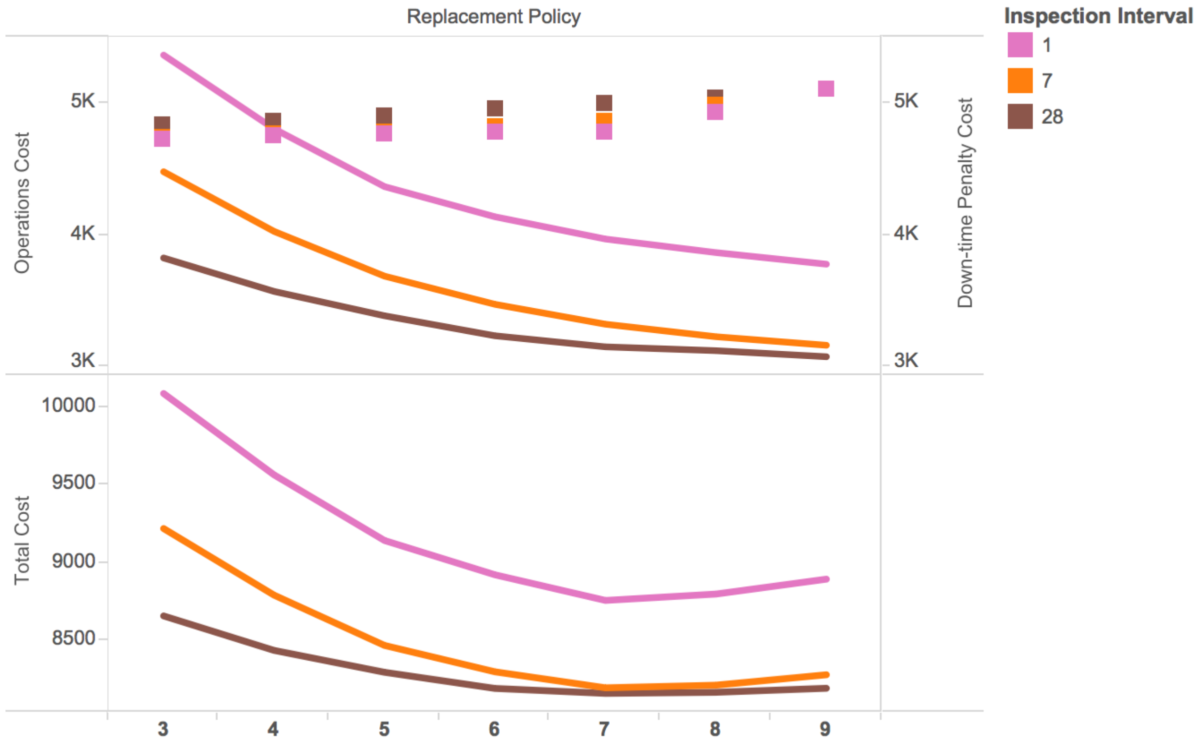

Figure 4.17: The trends of operations cost, down-time penalty cost and total cost for replacement policy. Color shows details about inspection interval. (P = P4(28), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $c_N = 100$, $r_d = 200$)

If we decrease r_c from 1 to 0.1 while keeping other parameters same as in Figure 4.17, we get the plot in Figure 4.18. We observe that when r_c is very low and when r_d is very high, $t_i = 1$ starts resulting in the minimum total cost.

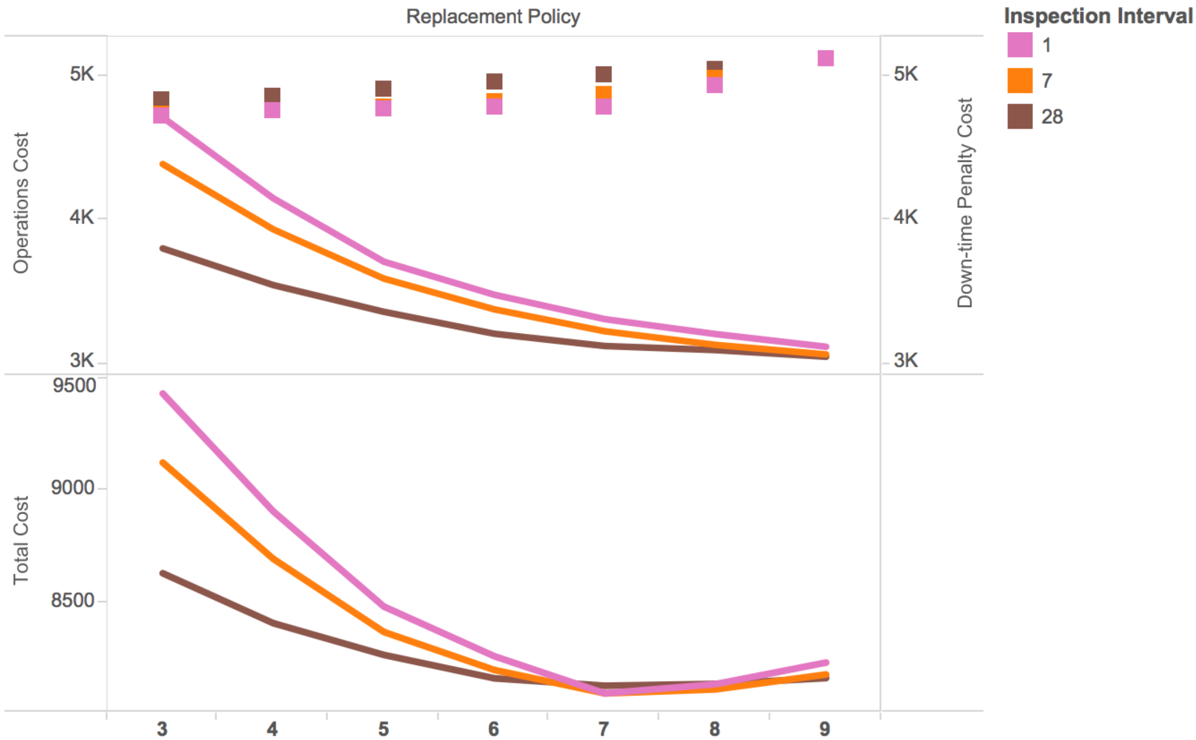

Figure 4.18: The trends of operations cost, down-time penalty cost and total cost for replacement policy. Color shows details about Inspection Interval. (P = P4(28), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 0.1$, $c_N = 100$, r_d =200, $c_o = 20$, $r_h = 0.25$)

4.2.2 Deriving Decision Plots

By varying the values of the key cost factors mentioned in Section 4.1.3, we can create boundary plots for this system. Similar to Section 4.1.3, we draw Decision Plots to help decide between $t_i = 1$ with IoT and $t_i = 7$ and no-IoT for P = P4(28). Table 4.3 shows the levels of factors used.

Factor	Levels Used
New Part Price (C_N)	10, 20, 30, 40, 50, 60, 70, 80, 90, 100
Down-time Penalty Cost Rate (r_d)	10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180, 190, 200
Manual Inspection Cost Rate (r_i)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Data Collection Cost Rate (r_c)	0.25, 0.50, 0.75, 1, 1.25, 1.50, 1.75, 2.0, 2.25. 2.5

Table 4.3: Factor levels used in generating the Decision Plots

Figure 4.19 shows the Decision Plot for down-time penalty cost rate (r_d) fixed at 10 units and manual inspection cost rate (r_i) fixed at 7 units for the system P = P4(28). At each intersection of the x and y axes we have a decision whether to choose IoT. The size of the marker is representative of the difference of the total costs between the IoT case and the no-IoT case, as a percentage of the no-IoT total cost (labeled as 'abs. % premium'). The color of the marker is red if the total cost for the IoT case is more than the total cost for the no-IoT case. The color of the marker is green otherwise.

We notice from Figure 4.19 that when r_i =7 and r_d = 10 and $r_d \leq 0.1$, the IoT case results in lower costs than the no-IoT option. This is evident from green markers in the figure region. We also observe that as the value of r_d decreases, the savings increase. Figure 4.20 shows side-by-side comparison of Decision Plots by varying the down-time penalty cost rate while keeping other factors fixed. Figure 4.21 shows side-by-side comparison of Decision Plots by varying the manual inspection cost rate while keeping other factors fixed. In both figures we see that number of green markers increase from left to right.

Figure 4.19: New part price vs. data collection cost rate. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. The marks are labeled by % change in total cost. (P = P4(28), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_i = 7$, $r_d = 10$, $c_o = 20$, $r_h = 0.25$)

Figure 4.20: New part price vs. data collection cost rate broken down by down-time penalty cost rate. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. (P = P4(28), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_i = 10$, $c_o = 20$, $r_h = 0.25$)

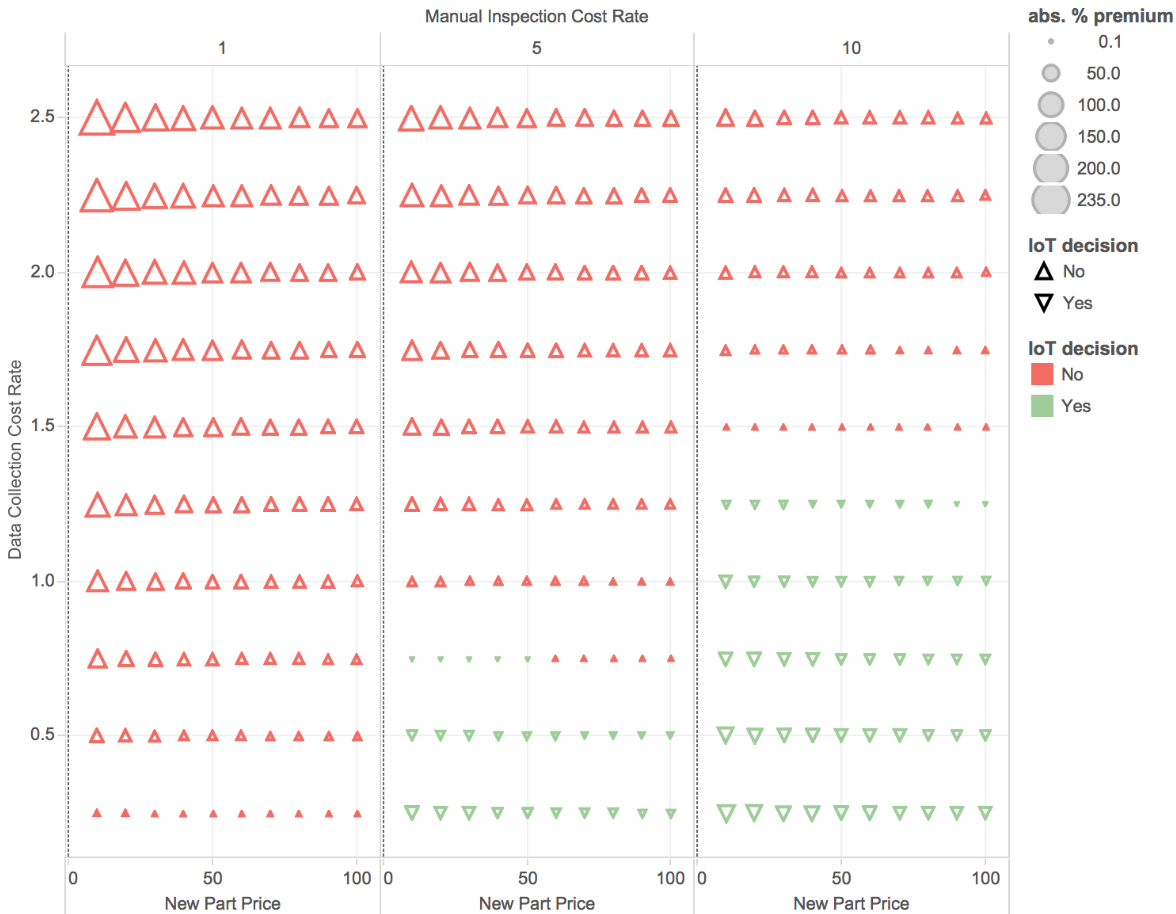

Figure 4.21: New part price vs. data collection cost rate broken down by manual inspection cost rate. Color shows details about IoT decision. Size shows details about abs. % premium. Shape shows details about IoT decision. (P = P4(28), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_d = 100$, $c_o = 20$, $r_h = 0.25$)

4.3 INVENTORY ANALYSIS:

In the example systems analyzed till this point, we fixed both the Inventory levels i.e., s and S (at the stocking location), the inventory holding cost rate, inventory ordering cost and the shipping costs. We have analyzed how the total cost varies with change in inspection intervals, replacement policies and cost factors like inspection costs, down-time penalty costs and data collection costs. In this sub-section, we explore how the changes in inventory policy affect the total cost.

Let us consider example system I. In Figure 4.4, we have fixed P = P3(21), $t_e = 1$, $t_s = 1$, $t_l = 5$, $S = 10$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 0.25$ and studied the trends of total cost, operations cost and down-time penalty cost to find the optimal replacement policy for different inspection intervals in IoT case. Now let us keep all the factors at same levels as in Figure 4.4 except S and study the trends of total cost for $t_i = 1$. Figure 4.22 shows the trend of total cost with S for different replacement policies. We observe that for any given S, the total cost is minimum when replacement policy is 7. Within the replacement policy 7, we observe that increasing S can minimize the total cost further. But after a point the total cost doesn't change much. This holds for any replacement policy shown in the figure. Until this point we haven't changed any cost factor from system I. Now if we increase the inventory holding cost factor from 0.25 to 1, we get the trends shown in Figure 4.23. For a given S again replacement policy 7 is optimal but for a given replacement policy, we observe that $S = 5$ or 6 results in minimum total cost.

By changing the underlying transition probability matrix in Figure 4.23, we generate Figures 4.24 and 4.25 which correspond to P = P2(31) and P = P1(62) respectively. One interesting aspect that we observe from Figures 4.23-4.25 is that with increase in MTTF, the sensitivity of total cost to S increases for a given replacement policy. We also observe that as the MTTF increases, the S value that achieves minimum cost for a given replacement policy decreases. The reason for this behavior is as the system becomes more reliable, maintaining more inventory only adds to the holding costs as the demand is low.

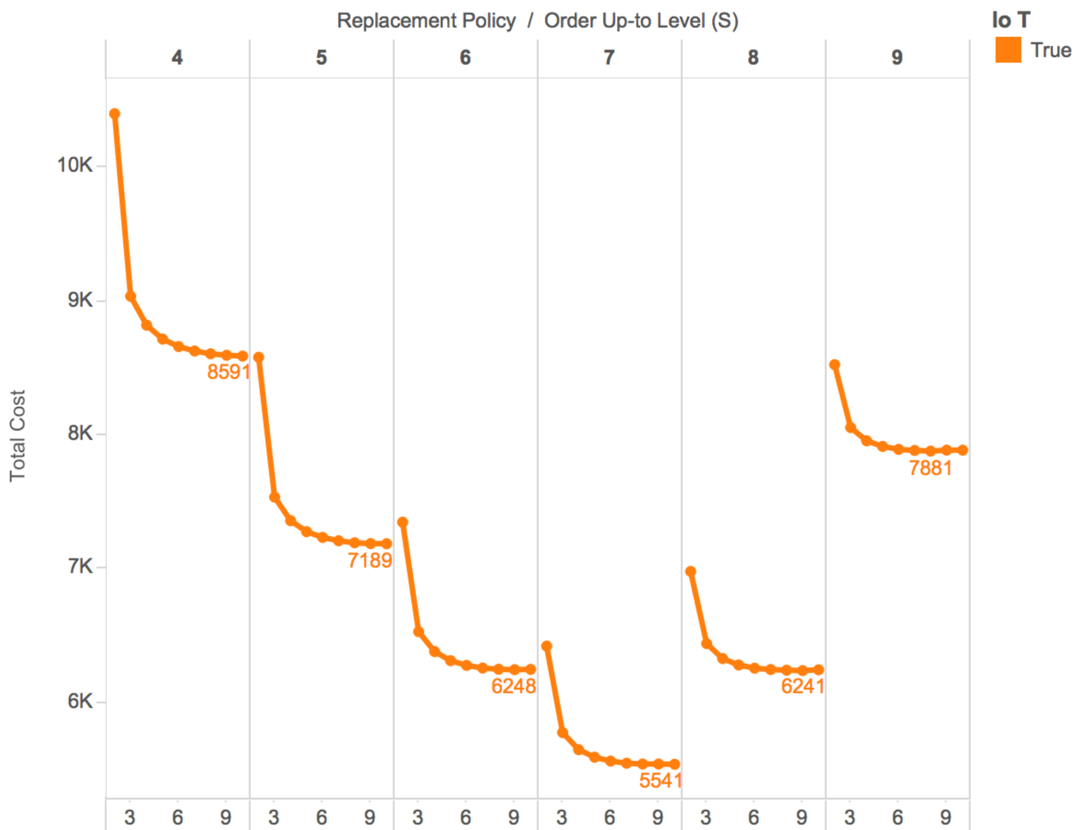

Figure 4.22: The trend of total cost for order up-to level (S) broken down by replacement policy. (P = P3(21), $t_e = 1$, $t_i = 1$, $t_s = 1$, $t_l = 5$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 0.25$)

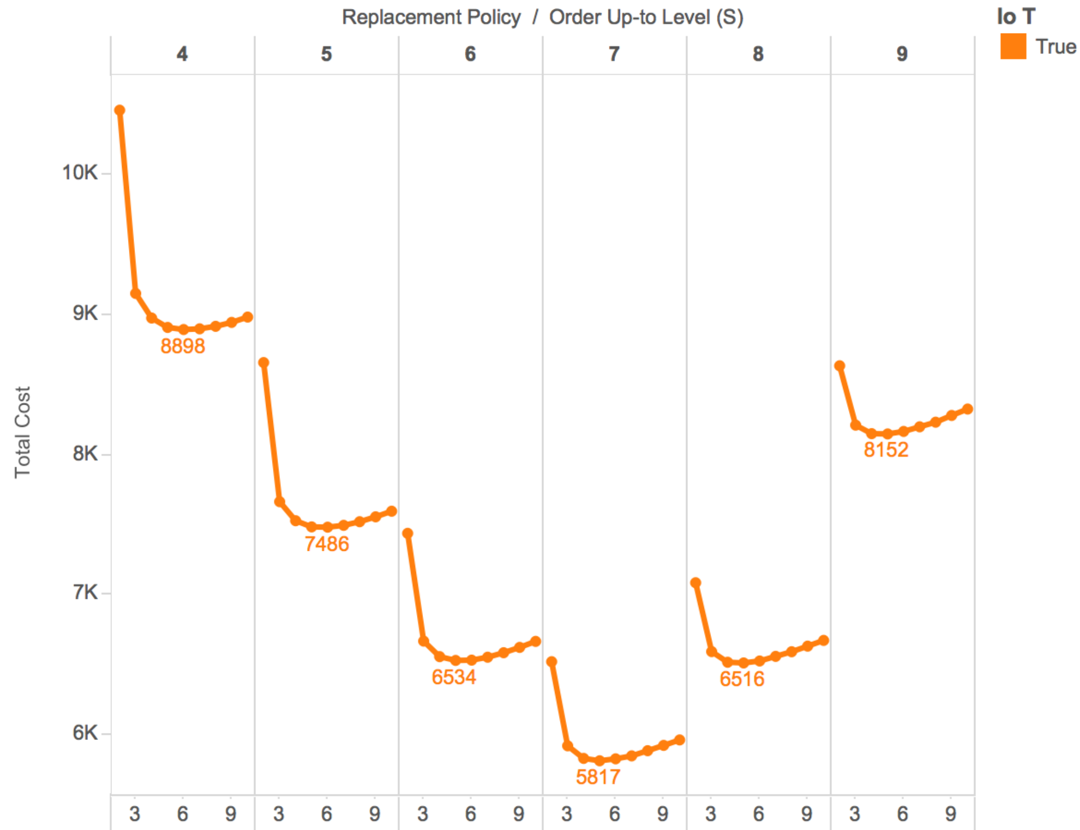

Figure 4.23: The trend of total cost for order up-to level (S) broken down by replacement policy. (P = P3(21), $t_e = 1$, $t_i = 1$, $t_s = 1$, $t_l = 5$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 1$)

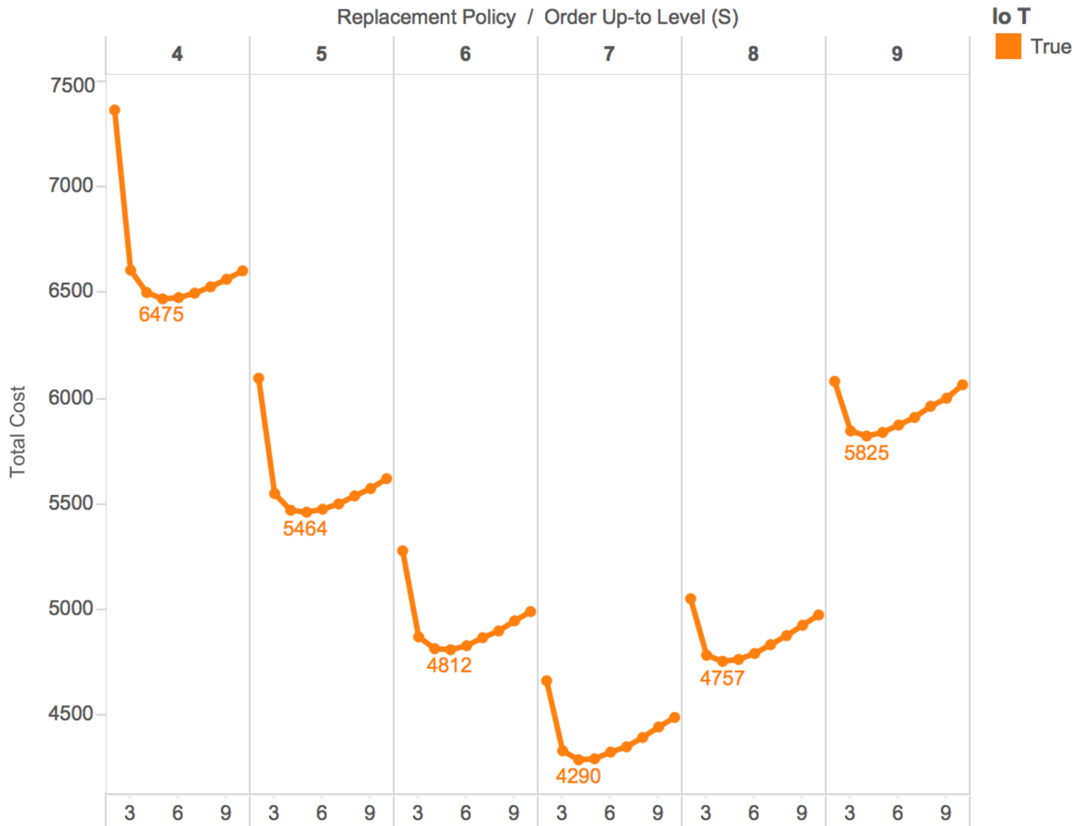

Figure 4.24: The trend of total cost for order up-to level (S) broken down by replacement policy. (P = P2(31), $t_e = 1$, $t_i = 1$, $t_s = 1$, $t_l = 5$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 1$)

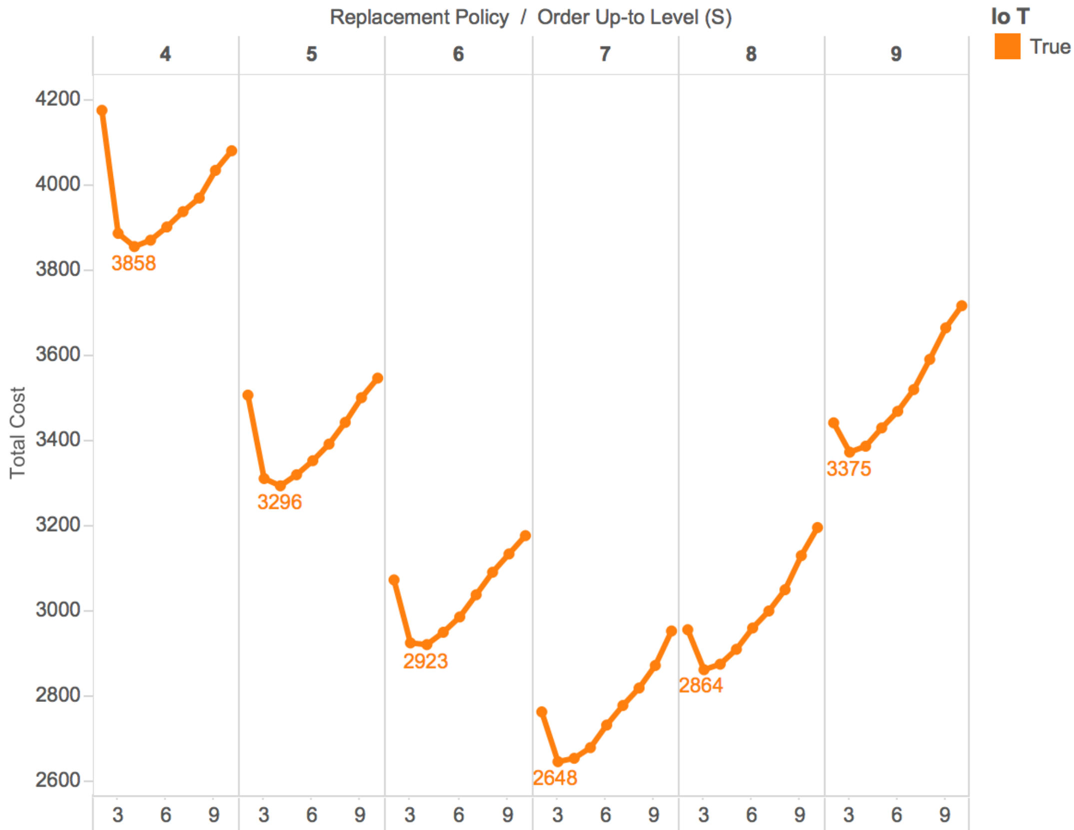

Figure 4.25: The trend of total cost for order up-to level (S) broken down by replacement policy. (P = P1(62), $t_e = 1$, $t_i = 1$, $t_s = 1$, $t_l = 5$, $s = 1$, $r_c = 1$, $c_N = 100$, $c_o = 20$, $r_d = 100$, $r_h = 1$)

Chapter 5: Conclusions and Future Work

5.1 Conclusions

In this work, we studied the effects of applying IoT based maintenance condition monitoring system to decide when to replace deteriorating parts in a stylized spare parts logistics system. Continuous data collection about the part health can enable early replacement policies which result in reduced total cost. IoT becomes more beneficial in the scenarios where the down-time costs are high and data collection costs are low. The data collection cost threshold where IoT becomes beneficial reduces with increase in MTTF of the parts in the system. In the systems with high holding cost, making inventory and replacement policy decisions jointly can be more beneficial.

5.2 Contributions

The major contributions of this work can be summarized as follows:

- A simulation based framework to study the effect of IoT-based maintenance condition monitoring system on a stylized spare-parts logistics system is introduced.
- Decision Plots that measure either the savings by applying IoT or increase in costs due to IoT are introduced and derived for several example systems.

5.3 Future Research Directions

In this work, we assumed that there is only one critical part per machine but in real word there are multiple critical parts in a machine. Extending this study to multiple part types and considering part dependencies and commonalities will be useful in making the study more valuable to the industry. The current simulation results are limited to two customers, hence including multiple customers with different shipping times is an important practical extension.

The current work takes a simulation based approach to find the optimum replacement policy for a given set of cost parameters. Developing analytical models to solve such problems can give us more insight. Re-evaluating stocking locations' location decisions after IoT is also a promising area to build the analytical models.

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