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A Study on the Effect of Protective Capacity on Cycle Time in Serial Production Lines

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A STUDY ON THE EFFECT OF PROTECTIVE CAPACITY ON CYCLE TIME

IN SERIAL PRODUCTION LINES

By

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This thesis investigates the interactions of several characteristics of serial production lines that contribute to production line performance. A full factorial experimental design of computerized simulations is conducted with three levels of downtime, four levels of variability, three levels of line length, three levels of constraint location, three levels of work-in-process, and six levels of protective capacity. This study enlarges upon recent four-workstation investigations and extends the knowledge to longer production lines. Some generalizations for the amount and location of protective capacity are drawn from the results, as a guide for process improvements and new production line design. An approximating regression model is constructed for prediction of cycle time outcomes with various values of contributing factors.

DEDICATION

This thesis is dedicated to all the members of my family who understood and supported me throughout this research.

ACKNOWLEDGEMENTS

The author's sincere appreciation is expressed to Dr. Bullington, Dr. Smyer, and Dr. Greenwood for their patience and guidance during the research described in this thesis. Appreciation is also expressed to Clay Walden for his invaluable help, genuine interest, and patience. The author would also like to thank Mr. Carl Brown, for his assistance with the computer hardware and software. Finally the author would like to express her appreciation to the faculty and staff of the Department of Industrial Engineering for accepting her as a student and a friend.

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CHAPTER I

INTRODUCTION

For many years the manufacturing industry has been fighting obstacles to high machine utilization and maximum production output from serial production lines. The historical line balancing technique is still being taught in institutions of higher learning; however, Just-In-Time (JIT) and Theory-Of-Constraints (TOC) strategies are also being introduced to Manufacturing / Industrial Engineering students today. Popular production operating strategies have also changed over time from Material Requirements Planning in the 1970's, to Just-In-Time and the Theory-of-Constraints in the 1980's and 1990's. Krajewski, King, Ritzman and Wong [11] refer to survey results in their 1987 paper that report only 9.5 percent of MRP users were successful in applying the MRP principles with the result that most deliveries were on time, and little or no expediting was necessary. Twenty years ago protection against uncertainty was obtained by increasing inventory. Customers could be served immediately, and production could make-to-stock. The popularity of JIT however, has lessened the attraction of increased inventory, especially finished goods inventories, due to the increasing awareness that the value added may not be realized if the finished goods are not sold before they become obsolete. Goldratt has pointed out that the cost of holding finished goods is actually much higher than previously believed [5]. Since the JIT and TOC approaches have become more common, managers are reducing inventories and exposing production problems which had previously been hidden by their considerable inventories. Now production personnel are trying to solve these problems.

Recently researchers have begun to study the characteristics of JIT and TOC serial production lines, and have attempted to identify factors that influence throughput and to what extent. Simulation experiments have been performed with varying amounts of line variability, machine downtime, Work-In-Process (WIP), and protective capacity, on JIT lines, TOC lines, and balanced production lines. Chakravorty and Atwater have conducted several studies [1, 21, 22, 23] and have established that protective capacity in a JIT line results in higher throughput than the same line without protective capacity [1]. Kadipasaoglu, Xiang, Hurley, and Khumawala studied different levels of protective capacity and their effects on throughput, establishing that higher levels of protective capacity can bring shorter cycle times [9]. Umble, Gray, and Umble have modeled a TOC line with a capacity buffer before and after the bottleneck, demonstrating the beneficial effect obtained with such an arrangement [16].

What is protective capacity? From the *APICS Dictionary*, protective capacity is "a given amount of extra capacity at non-constraints above the system constraint's capacity, used to protect against statistical fluctuations (breakdowns, late receipts of material, quality problems, etc.)" [17 by reference in 1].

The only studies of protective capacity known to the author at the time of this writing are the studies mentioned above. The purpose of this research is to gain a better understanding of the benefits of protective capacity in serial production systems, including how these benefits vary with changes in constraint location, line length, work-in-process levels, downtime levels, and coefficient of variability levels. Table 2 on page 13 summarizes the protective capacity research and Table 5 on page 20 includes the research parameters for this study. The literature review discusses the reasoning for selection of the levels of variability, downtime, constraint location, and WIP.

Simulation Experimental Design

The research is designed to further investigate the extent of the effect of varying levels of protective capacity on throughput while also varying the number of stations in the production lines. A 6 x 3 x 4 x 3 x 3 x 3 (1944) full-factorial ANOVA design with 6 levels of protective capacity (PC), 3 levels of machine downtime (DT), 4 levels of line variability (CV), 3 levels of Work-In-Process (WIP), 3 levels of constraint location (CL), and 3 levels of line length (ST) is studied.

CHAPTER II

LITERATURE REVIEW

Eppen, Martin, and Schrage in cooperation with General Motors, built a model involving three scenarios based on forecast demand. Their purpose was to discover which features of the U.S. manufacturing environment needed the most attention. Their study identified lot sizes, setup times, workforce flexibility, yield losses, product customization, and product structure, some of which were more likely to have better payoff than others [4]. These factors continue to contribute to design and production challenges today. Some U.S. companies have enlisted Japanese manufacturers' assistance in implementing JIT in their (U.S.) plants. Seemingly, JIT is the way of the future of manufacturing. It has also been pointed out in the literature that JIT evolved over a period of years, and of course, U.S. companies cannot expect to achieve the same results overnight.

The underlying motivation for all of these approaches is to produce more profit, faster, with less expense, with less effort, and less confusion, if at all possible. In the recent past and in some current manufacturing environments, many production orders required expediting to meet the promised delivery date, while in the process of meeting one schedule, another is missed. Years of industrial experience have not solved the problem of unexpected events taking place and disrupting finely tuned production plans.

Since Goldratt's The Goal [5], terms like variability, statistical fluctuations, bottleneck, and constraint are becoming familiar to operations engineers and managers, and there seems to be a merging of JIT and TOC philosophies in some companies.

One obvious aspect of the JIT system is that the product flow is usually in very small lot sizes, sometimes as low as 1. This comes with a high risk for most producers who are accustomed to long setup times and unexpected lengthy downtimes. The Japanese answer to this is to reduce variability in the process, minimize setup, and to schedule regular preventive maintenance, nearly eliminating significant disruptions in the product flow. Goldratt's answer is protective capacity and letting the constraint set the production rate. He advocates sufficient WIP either side of the bottleneck to minimize the effect of upstream or downstream interruptions [5]. Buss, Lawrence and Kropp [3] link in-process congestion costs to lack of coordination between production capacity and demand volume planning. They point out that the traditional assumption that capacity utilization rates of 100 percent are feasible is actually producing more delay in cycle times. Many articles exist discussing the benefits of buffers to smooth the flow between workstations either in manual lines, or in automated ones, most of which assume buffers between each pair of workstations.

Martin [13], states that buffer capacities as well as the optimum number of workstations should be designed into the line. He describes a mathematical model and an algorithm for obtaining the optimal number of workstations (N*) and buffer capacities (B*). In the evaluation of his model, Martin graphically describes the relationship of these two factors to profit, efficiency, wage costs, space costs, and holding costs. His profit diagram indicates that N* and B* have little effect on profit, when B>0; that for efficiency larger buffers are preferred; and the three cost factors (WIP, space, and wages) increase when buffers are increased. This seems to indicate that smaller buffers are better. Hillier [6] describes the storage bowl phenomenon for buffer capacities; that is, the first and last stations have the smallest buffers and they grow successively larger by one unit, towards the center of the line. This configuration produces an optimal production rate for lines with a balanced workload. For unbalanced lines the bottleneck drives the throughput, so buffer capacities need to protect the bottleneck from starving and blocking. Hillier's suggestion for this situation is that beginning with the predicted bowl pattern, quantities should be decreased at all buffers not adjacent to the bottleneck. Production planners who historically have little education in this area can easily adopt this type of "rule-of-thumb."

Hurley and Whybark [8] also discuss buffer capacity and location as part of line design. Their simulations test the effect of different buffering techniques on capacity utilization, throughput, and cycle time. Their studies suggest that variance reduction and capacity increases can replace high inventory for buffering between demand and production. Umble, Gray and Umble [16] explain how the theory of constraints' Drum-Buffer-Rope system allows manufacturing operations to compensate for machine downtimes, changeovers, and other stoppages to the product flow, with buffers on either side of the bottleneck. Their simulation models expose the effect of changeovers, and various buffer strategies, by testing a 17-station line with varying process times under five scenarios:

(1.) Pull system with WIP=1 at each buffer;

(2.) Pull system with WIP=2 at each buffer;

(3.) TOC buffer strategy with buffers only at the constraint resource;

(4.) Pull system of (1) with added changeovers after 120 units;

(5.) TOC strategy of (3) with added changeovers after 120 units.

Each case was run for a simulated 100 one-week periods (100 replications) of seven 24-hour days. Unplanned interruptions were randomly generated and throughput was recorded; results are tabulated in Table 1. The time buffer was planned for 144 minutes before the constraint, and the space buffer for 12 units (144 minutes of processing time) after the constraint. It is interesting to note that in each of the TOC (Drum-Buffer-Rope) cases (3 and 5), the buffers before and after the constraint contributed more to throughput than buffers at each location, cases 1, 2, and 4.

Table 1. Summary of Umble, Gray & Umble Study

Case Description, Ideal Output = 778 units	Actual Output	Percent of Ideal Output	Percent Lost Output (from ideal)
1. Pure pull system	653.6	78.8	21.2
2. Kanban=2	710.5	85.7	14.3
3. TOC buffers at constraint only	753.1	90.9	9.1
4. Pure pull with changeovers after 120 units	414.5	50	50
5. TOC buffers with changeovers after 120 units	487.3	60	40

Where cases 1 and 2 have buffers of 1 and 2 units of WIP respectively, cases 3 and 5 have no buffer except for the two one-hour allowances immediately before and after the constraint. Case 3 (DBR) showed more throughput than either case 1 or case 2. Although cases 4 and 5 experienced significant degradation of productive capacity due to changeovers, case 5 (DBR) again showed more throughput than the balanced buffer lines, as evidenced by 10% more output than case 4.

There is much literature on the location and allocation of space to buffers, and all seem viable. But, the reason for all this buffering is the uncertainty, or variability of demand, coupled with unexpected interruptions caused by equipment downtimes, and re-ordering of job priorities. The Japanese state that they have minimized variability, and control what remains. Products are made to order rather than made to stock, which eliminates expediting and priority interruptions. Also, in Japanese JIT systems, operations managers are not opposed to letting machines or workers sit idle while other stations are running. It has been brought out that some JIT plants incorporate a protective capacity of up to 18% [9]. Kadipasaoglu, Xiang, Hurley, and Khumawala [9], state that protective capacity reduces the need for buffer inventory, and accommodates changes in the product mix and customer orders.

Of particular interest, then, is the capacity designed into the workstations of the production line, and the allowances made to incorporate variability. Few studies have been published in this area; however, those that have seem logical, repeatable, and in agreement with each other. Atwater and Chakravorty [1] cite Goldratt as insisting that managers producing with low stocks of inventory must have protective capacity to ensure reliable delivery. Following are summaries of the key protective capacity studies referenced.

The Atwater and Chakravorty Simulation Study

Atwater and Chakravorty construct a simulation model and use it to investigate the effect of differing levels of protective capacity. Using various levels of system variability and resource downtime, the interactions between them with varying levels of protective capacity were observed. This Atwater and Chakravorty model consisted of two line designs, one with protective capacity and one without. Both lines were subjected to two levels of variability (5% and 50%), two levels of downtime (10% and 30%), and eight levels of inventory (WIP = 10, 20, …80 units). Statistics were collected from the simulation models for 20,000 minutes after reaching steady-state. Downtime was modeled with an exponential distribution for occurrences and a lognormal distribution for duration, considering the repair time as a process. The simulation was run with WIP held constant throughout the run. Queues were sized to prevent blocking, and the same seed was used for both line designs in order to subject each line to identical conditions. Cycle time was the dependent variable. Processing time was modeled using a lognormal distribution, citing Dudley, Muralidhar, and Mitra [18, 19, 20 by reference in 1, 22, 23, 24] as establishing the log-normal distribution as representative of real-world processing times. The levels of variability combined with the protective capacity provided four environments for operations: high variability with and without protective capacity, and low variability with and without protective capacity. The performance of these environments with varying levels of WIP and downtime were recorded and analyzed using an ANOVA model.

With protective capacity, lower cycle times were achieved in all environments. The lines with protective capacity stabilized with a lower level of inventory producing a lower cycle time. With higher levels of inventory, the lines without protective capacity did stabilize, at a slightly longer cycle time. Predictable performance is desirable for management decisions affecting customer service (lead times). The ANOVA showed significance (p>F of 0.0001 or less) for line design (LD), system variability (SV), WIP, LD and SV, LD and WIP, SV and WIP, and LD and SV and WIP [1]. There is a tradeoff between the cost of increasing protective capacity and the cost of holding higher WIP.

<u>The Kadipasaoglu, Xiang, Hurley, and Khumawala Simulation Study</u>

Kadipasaoglu, Xiang, Hurley, and Khumawala [9] report from their simulation studies the effect of the inclusion of a constraint, location of the constraint, the amount of protective capacity, and the interactions between them with varying levels of resource downtime and system variability. Workstation processing times were modeled with the lognormal distribution, which is consistent with Atwater and Chakravorty's studies. The hypothesis of the Kadipasaoglu, et al., study is that protective capacity and time buffers in front of the constraint will lead to shorter cycle times with less inventory, which is consistent with the literature. This study used a coefficient of variation of 0.1, 0.2, and 0.3, with protective capacity varying from 0% to 37.5% in 12.5% increments. Downtime was modeled at 10, 15, and 20%, utilizing the lognormal distribution for repair (process) times. Kadipasaoglu, et al.'s simulated the system for 350,000 minutes (two years of operation). While Atwater and Chakravorty established experimentally that protective capacity improves performance, specifically flow time, Kadipasaoglu, et al., begin to establish the extent of that effect in various manufacturing environments.

The Kadipasaoglu, et al., ANOVA indicated that all factors are significant. Non-constraint downtime was the most significant factor influencing cycle time. Protective capacity significantly reduced cycle time when used in a high downtime system, while 0% protective capacity showed a "wandering" constraint. These results are consistent with the Drum-Buffer-Rope strategy. The Kadipasaoglu, et al., experiments confirmed that the more the variability the longer the cycle time; however, adding protective capacity diminishes this effect. Constraint location was not a significant factor with high constraint downtime; while at lower levels of constraint downtime, location has a visible effect on performance. The best location for the constraint is at the beginning of the line. When non-constraint downtime is low, constraint location was not a significant factor, while as non-constraint downtime increases, so does the improvement due to locating the constraint near the beginning of the process. Locating the constraint near the beginning of the process and also having protective capacity, together contribute to improved performance. Kadipasaoglu, et al., conclude that the extent of the improvement from protective capacity is dependent on variability and system downtime. Increasing protective capacity is beneficial with diminishing returns.

Other Studies

In a study of a plant with multiple production lines, Kim [10]attempts to incorporate into the line design enough capacity to ensure stability of product flow to overcome the effects of uncertainties in demand and actual production. Kim develops a mathematical formula for choosing the capacity level allocated to each production line, and an inventory level for each product, to minimize the total capacity and operating costs subject to an investment budget constraint. He points out that there is a cost tradeoff between capacity level and base stock level needed for each product in the line. Kim begins his allocation by assigning a threshold capacity determined by his formulae, to each line. This threshold capacity ensures the stability of the queue. Additional excess capacity is allocated in proportion to the square root of the product of variability and cost factors. Generally, Kim advocates giving less processing capacity to the stable products by stocking them, and more capacity to unstable products to prevent a large amount of safety stock and back orders. He also describes a tradeoff between product grouping, which reduces variability because of pooling, and effective capacity loss due to changes over time. These features of a production plant must be evaluated for each individual facility. The simulation studies discussed above are summarized in Table 2.

Making comparisons among these studies is difficult, as they all have assorted features, i.e. numbers of stations, levels of variability, and protective capacity. However, they indicate a direction for more work. Further studies of protective capacity and its ability to diminish the effects of variability, uncertainty, material delays, and any other unexpected events are needed. A methodical approach to include all factors is desirable and may lead to a rule-of-thumb or other predictive relationship among the factors.

Table 2. Summary of Simulation Studies

Variable ? Author ?	Protective Capacity Level	Variability, % of Mean Process Time	Downtime on all Work-Stations, % of Simulation Run Time	WIP	Simulation Time	Work-stations	Response Variable(s)
Atwater and Chakravorty	0%, 18% of mean process time	5% 50%	10% 30%	10, 20, 30, 40, 50, 60, 70, and 80 units	20,000 minutes, 10 replications	4, 5	Cycle Time
Kadipasaoglu et al	0%, 12.5%, 25%, 37.5% of mean process time	10%, 20%, 30%	10%, 15%, 20%	Response variable	350,000 minutes, 10 replications	4	Cycle Time, WIP
Umble, Gray, and Umble	144 minutes before and after constraint	Not specified	6.5%	1) 17 Max, 2) 34 Max, 3) 39 units Max, (12 on each side of the bottleneck)	10,080 minutes, 100 replications	17	Cycle Time

CHAPTER III

METHODOLOGY

A consistent and planned approach to isolating variables could provide useful insight. Therefore, a full factorial experimental design was used to conduct the simulation experiment, incorporating increments of variability (CV), protective capacity (PC), work-in-process (WIP), number of workstations (ST), constraint location (CL), and downtime (DT), while measuring cycle time as the response variable. Because the Atwater and Chakravorty study revealed that there is a tradeoff between the cost of increasing protective capacity and the cost of holding higher WIP, the simulation model used in this thesis reflects three levels of WIP; two, five, and ten units per workstation. Queues are sized to hold total WIP in the system, as was done in the Atwater and the Kadipasouglu, et al., studies. Simulation model details are shown in the appendix as Figure 28, and Tables 12 through 14; a descriptive overview is provided here.

Downtime in the previous studies was modeled at ten, fifteen, twenty, and thirty percent, utilizing the lognormal distribution for repair (process) times, and the exponential distribution for time between failures. The simulation experiments in this study are modeled at zero, ten, and thirty percent downtime, with the same mean time to repair, and mean time between failures, as were used in the Atwater and Chakravorty and the Kadipasaoglu, et al., studies. The exponential distribution was used for time between failures, and the lognormal distribution was used for the repair time, which are the same distributions as those used in the two studies referenced above. The coefficient of variation of process times is set at four levels; five, fifteen, twenty-five, and fifty percent, to cover the entire range of values studied in the two previous studies. Constraint location is modeled at the first station, the last station, and at the midpoint of the line. For the five- and fifteen-station lines, there is an actual midpoint, the workstation with an equal number of workstations on either side of it. For the ten-station line, however, no true midpoint exists, and the fifth station was selected as the point for the constraint location designated as "middle." The levels of protective capacity in the study used for this thesis are chosen to cover an incremental range of values from zero to forty percent, covering the entire range of the Kadipasaoglu, et al., studies.

Additional assumptions are that tests are run on dedicated lines with only one product, that non-bottleneck stations all have the same level of protective capacity for a given simulation run, and that repair processes begin when they occur with no waiting time.

The parameters selected are designed to provide data that will complement the existing studies, and to extend the knowledge to longer flow lines (lines with more workstations). This research investigates the effect of protective capacity relative to the presence of various levels of other production line variables. Specifically, this research is designed to answer these questions:

1. Do longer lines (more workstations) require more protective capacity than shorter lines?

2. For what conditions does cycle time benefit from the presence of protective capacity?
3. Does the level of work-in-process affect protective capacity's ability to obtain improved cycle times?
4. Is there a numerical relationship between serial line operating conditions and the level of protective capacity needed for reduced cycle time?

ProModel 4.2 was used to develop the simulation models. Reproducing the initial conditions used by Atwater & Chakravorty, work-in-process was distributed evenly across all workstations at initialization of the model. A 4200-hour (252,000 minutes), warm-up period was allowed, followed by 4200 hours (252,000 minutes), of run time, during which statistics were collected. It was determined from the procedure of Law and Kelton [24], utilizing Equation (1), that i >6.0205 replications would be sufficient for greater than 95% confidence in each response. This is based on α= 0.01 selected for 99% confidence in each individual replication's mean cycle time, and γ'= 0.047619 for an approximate relative error of 5% in the overall mean cycle time of all replications for each scenario. That is, γ=0.05 desired relative error, which is approximated by using γ'=(0.05)/1.05, for γ'= 0.047619. Ten replications were run of each combination of factors.

$$i \geq S^2(n)\left[\frac{Z_{(1-a/2)}}{g'\overline{x}(n)}\right]^2 \qquad \text{Equation (1)}$$

where α= 0.01, and γ'= 0.047619, s(n) and x(n) are taken from the sample run of 10 replications of the worst-case scenario (n=10).

Figure 1 illustrates the flow line that was modeled, with an exponential distribution for time between failures (MTBF), and a lognormal distribution for time to repair (MTTR), considering repair time as a process as discussed by authors of previous studies [1, 9, 19, 20], and demonstrated in both previous protective capacity studies mentioned above. An effort has been made to design this study to extend the work of the previously published studies, by the application of this concept to longer flow lines. For this reason, many of the conditions for conducting the simulations were chosen to duplicate the earlier studies. The conditions studied are constant work-in-process (CONWIP) applications, where as each entity exits the system, a new entity enters at the first workstation, maintaining the desired level of work-in-process.

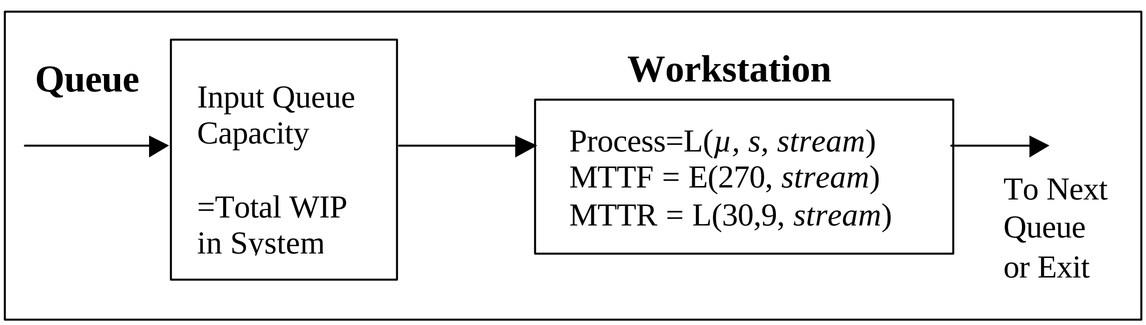

Figure 1. Processing and Downtime Distributions Set-up for Each Workstation

Mean process time was set at 10 minutes for the constraint, and at 9.5, 9, 8, 7, and 6 minutes at the other stations for the 5, 10, 20, 30, and 40 percent levels of protective capacity, respectively. Each factor level is shown in Table 4.

Ten replications were made for each of the experimental combinations for a total of 19,440 simulation runs. Common random numbers were employed so that each set of experimental factors would experience the same conditions, enabling better comparisons. Specifically, distinct random number streams were selected for each distribution at each workstation, and these streams were used in the same location in all experiments.

As a means of validating the modeling conditions, the author initially repeated the Atwater and Chakravorty experiments, with 4 stations for 0% protective capacity, and 5 stations for 18% protective capacity, with high and low variability, and high and low downtime. Atwater and Chakravorty reported their findings as time between exits, taking the total run time divided by the number of exits. The chart below shows the Atwater and Chakraavorty results and the results of the repeated study conducted in ProModel. This author obtained nearly the same results with little or no significant difference.

Table 3. Summary of Validation Studies

	0% Protective Capacity, 4 Stations				18% Protective Capacity, 5 Stations			
Variability	10% Downtime		30% Downtime		10% Downtime		30% Downtime	
Study	Atwater	Sloan	Atwater	Sloan	Atwater	Sloan	Atwater	Sloan
5%	11.7	11.72	16.4	16.13	11.1	11.2	15.2	15.1
50%	12.1	12.19	16.5	16.7	11.7	11.35	15.5	15.53

The model was then extended to 5, 10 and 15 workstations. Cycle time for each of 10 replications was recorded. Ten replications were made for each of the experimental combinations for a total of 19,440 runs. Table 5 adds this research to the summary of simulation studies shown in Table 2.

Table 4. Experimental Factors

Experimental Factor	Levels Tested
Downtime, DT	0%, 10%, 30%
Work-in-Process, WIP	2, 5, and 10 Units per Workstation
Coefficient of Variation, CV	0.05, 0.15, 0.25, 0.50
Number of Workstations, ST	5, 10, 15
Constraint Location, CL	Beginning, Middle, and End of Line
Protective Capacity, PC	0%, 5%, 10%, 20%, 30%, 40%

Table 5. Summary of Simulation Studies Including This Research

Variable ? Author ?	Protective Capacity Level	Variability, % of Mean Process Time	Downtime on all Work-Stations, % of Simulation Run Time	WIP	Simulation Time	Work-stations	Response Variable(s)
Atwater and Chakravorty	0%, 18% of mean process time	5% 50%	10% 30%	10, 20, 30, 40, 50, 60, 70, and 80 units	20,000 minutes, 10 replications	4, 5	Cycle Time
Kadipasaoglu et al	0%, 12.5%, 25%, 37.5% of mean process time	10%, 20%, 30%	10%, 15%, 20% on constraint and on non-constraints	Response variable	350,000 minutes, 10 replications	4	Cycle Time, WIP
Umble, Gray, and Umble	144 minutes before and after constraint	All one product vs changeovers after 120 units are produced.	6.5%	1) 17, 2) 34, 3) 39 units, 12 on each side of the bottleneck	10,080 minutes, 100 replications	17	Cycle Time
Thesis Research <u>Sloan</u>	0%, 5%, 10%, 20%, 30%, 40% of mean process time	5%, 15%, 25%, 50%	0%, 10%, 30%	<u>Stations</u>: WIP <u>5</u>: 10, 25, 50 <u>10</u>: 20, 50, 100 <u>15</u>: 30, 75, 150	252,000 minutes, 10 replications	5, 10, 15	Cycle Time

CHAPTER IV

ANALYSIS AND RESULTS

The ANOVA results are included as Table 6. Significance was found with 5 of 6 main effects, 13 of 15 two-way interactions, 15 of 20 three-way interactions, 9 of 15 four-way, and 2 of 6 five-way interactions. The main effects will be discussed first, followed by interactions. Because of the amount of information, remarks will be limited to the more significant interactions. Plots of the significant actions or interactions are utilized to visualize the direction of the effects.

Main Effects

It is not surprising to note that increasing downtime, WIP, variability, and line length increase cycle time. Neither is it surprising that increasing protective capacity decreases cycle time. It is the interaction of these factors that is of particular interest. However, a few general observations can be made from the graphs of the main effects.

Work-In-Process

The most significant main effect is that of WIP level. From Figure 2 we can see a significant increase in cycle time from WIP=2 to WIP=5 of 115%, and from WIP=5 to WIP=10 of 316%. Clearly, WIP level must be chosen judiciously.

Table 6. ANOVA Results

Dependent Variable: CT

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1942	5323286385.52987000	2741136.14084957	96421.04	0.0001
Error	17497	497419.03273392	28.42881824		
Corrected Total	19439	5323783804.56260000			

	R-Square	C.V.	Root MSE	CT Mean
	0.999907	0.758758	5.33186818	702.71011338

Source	DF	Anova SS	Mean Square	F Value	Pr > F
DT	2	363189875.84525600	181594937.92262800	99999.99	0.0001
WIP	2	2750145908.40468000	1375072954.20234000	99999.99	0.0001
CV	3	357318.41120911	119106.13706970	4189.63	0.0001
ST	2	1618681930.00256000	809340965.00128100	99999.99	0.0001
CL	2	257.43725967	128.71862984	4.53	0.0108
PC	5	10859722.82381820	2171944.56476364	76399.40	0.0001
DT*WIP	4	40649169.29911610	10162292.32477900	99999.99	0.0001
DT*CV	6	28779.16518021	4796.52753003	168.72	0.0001
DT*ST	4	64201971.23255540	16050492.80813880	99999.99	0.0001
DT*CL	4	1124.13394737	281.03348684	9.89	0.0001
DT*PC	10	8217578.64568710	821757.86456871	28905.80	0.0001
WIP*CV	6	36593.32896805	6098.88816134	214.53	0.0001
WIP*ST	4	453534464.83485900	113383616.20871400	99999.99	0.0001
WIP*CL	4	486.15296364	121.53824091	4.28	0.0019
WIP*PC	10	857744.41020966	85774.44102097	3017.17	0.0001
CV*ST	6	66490.16287231	11081.69381205	389.80	0.0001
CV*CL	6	113.21993446	18.86998908	0.66	0.6790
CV*PC	15	203234.60402679	13548.97360179	476.59	0.0001
ST*CL	4	785.92326736	196.48081684	6.91	0.0001
ST*PC	10	2366691.99860573	236669.19986057	8324.97	0.0001
CL*PC	10	5662.49444962	566.24944496	19.92	0.0001
DT*WIP*CV	12	9172.87935829	764.40661319	26.89	0.0001
DT*WIP*ST	8	6183513.25013733	772939.15626717	27188.58	0.0001
DT*WIP*CL	8	450.06207275	56.25775909	1.98	0.0449
DT*WIP*PC	20	1169736.45423698	58486.82271185	2057.31	0.0001
DT*CV*ST	12	5611.87911797	467.65659316	16.45	0.0001
DT*CV*CL	12	262.99588394	21.91632366	0.77	0.6813
DT*CV*PC	30	25220.01453590	840.66715120	29.57	0.0001
DT*ST*CL	8	1587.08408356	198.38551044	6.98	0.0001
DT*ST*PC	20	2037325.54156494	101866.27707825	3583.20	0.0001
DT*CL*PC	20	0.00000000	0.00000000	0.00	1.0000
WIP*CV*ST	12	7268.41175842	605.70097987	21.31	0.0001

(continued)

Table 6. ANOVA Results (continued)

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Analysis of Variance Procedure

Dependent Variable: CT

Source	DF	Anova SS	Mean Square	F Value	Pr > F
WIP*CV*CL	12	232.47038651	19.37253221	0.68	0.7711
WIP*CV*PC	30	247930.72155571	8264.35738519	290.70	0.0001
WIP*ST*CL	8	627.25324631	78.40665579	2.76	0.0048
WIP*ST*PC	20	0.00000000	0.00000000	0.00	1.0000
WIP*CL*PC	20	176666.55933952	8833.32796698	310.72	0.0001
CV*ST*CL	12	167.80386734	13.98365561	0.49	0.9209
CV*ST*PC	30	58142.21275330	1938.07375844	68.17	0.0001
CV*CL*PC	30	14170.04055595	472.33468520	16.61	0.0001
ST*CL*PC	20	3599.57934952	179.97896748	6.33	0.0001
DT*WIP*CV*ST	24	1676.52416611	69.85517359	2.46	0.0001
DT*WIP*CV*CL	24	257.10032082	10.71251337	0.38	0.9975
DT*WIP*CV*PC	60	215141.99976730	3585.69999612	126.13	0.0001
DT*WIP*ST*CL	16	923.96212006	57.74763250	2.03	0.0086
DT*WIP*ST*PC	40	384378.16411972	9609.45410299	338.02	0.0001
DT*WIP*CL*PC	40	103289.36501312	2582.23412533	90.83	0.0001
DT*CV*ST*CL	24	384.84500694	16.03520862	0.56	0.9564
DT*CV*ST*PC	60	70292.93976402	1171.54899607	41.21	0.0001
DT*CV*CL*PC	60	0.00000000	0.00000000	0.00	1.0000
DT*ST*CL*PC	40	48636.43027687	1215.91075692	42.77	0.0001
WIP*CV*ST*CL	24	289.05939865	12.04414161	0.42	0.9938
WIP*ST*CL*PC	40	0.00000000	0.00000000	0.00	1.0000
WIP*CV*CL*PC	60	521235.30646324	8687.25510772	305.58	0.0001
WIP*CV*ST*PC	60	0.00000000	0.00000000	0.00	1.0000
CV*ST*CL*PC	60	13356.18062210	222.60301037	7.83	0.0001
DT*WIP*CV*ST*CL	48	705.71735001	14.70244479	0.52	0.9977
DT*WIP*CV*ST*PC	120	0.00000000	0.00000000	0.00	1.0000
DT*WIP*CV*CL*PC	120	507055.02440834	4225.45853674	148.63	0.0001
DT*WIP*ST*CL*PC	80	0.00000000	0.00000000	0.00	1.0000
DT*CV*ST*CL*PC	120	176871.75464821	1473.93128874	51.85	0.0001
WIP*CV*ST*CL*PC	120	0.00000000	0.00000000	0.00	1.0000
DT*WIP*CV*ST*CL*PC	239	0.00000000	0.00000000	0.00	1.0000

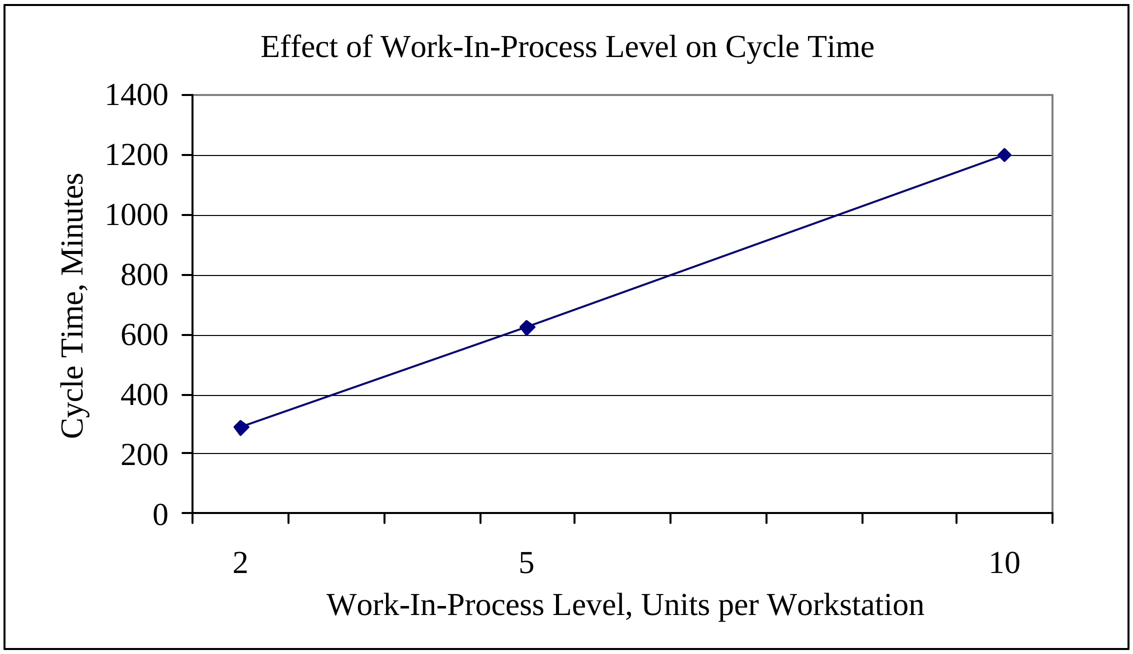

Figure 2. Effect of WIP on Cycle Time

Line Length

Identified in this study as number of workstations (ST), line length was the next most significant factor. Figure 3 shows a linear increase in cycle time, due to the increase in line length. To eliminate the effect of the increase in processing time due entirely to the number of workstations, cycle time is divided by the number of workstations, to provide a "rated" value for comparison (see Figure 4). For the rated data, there is almost a flat plot, indicating that the number of workstations, in and of itself, is not of significant influence on cycle time, aside from the additive effect of processing times.

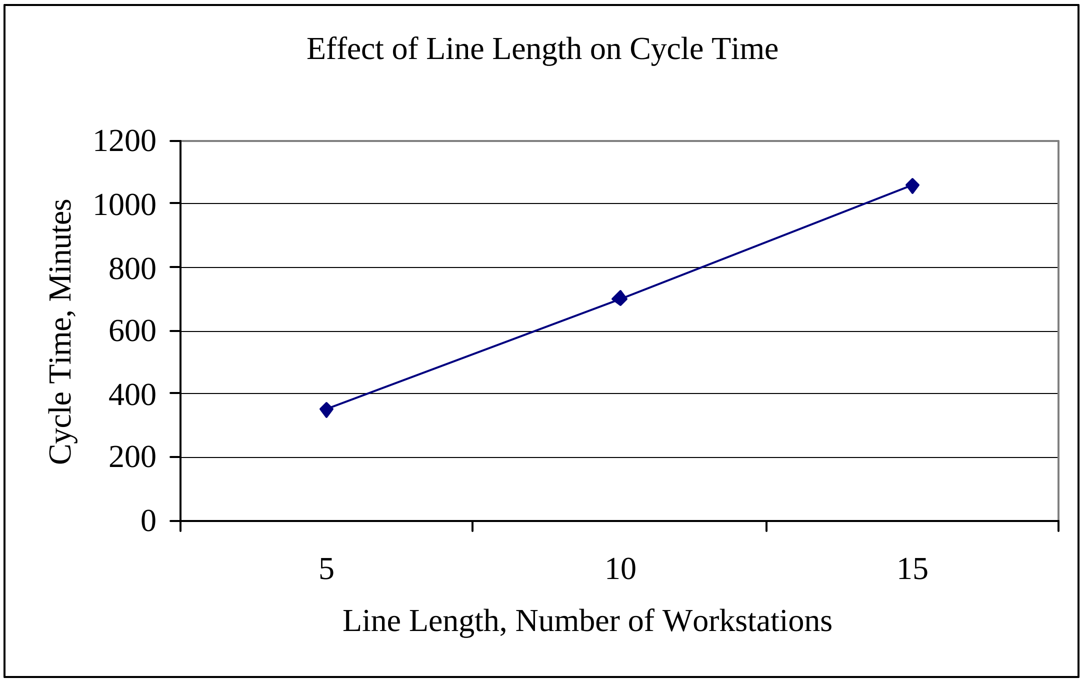

Figure 3. Effect of Line Length on Cycle Time

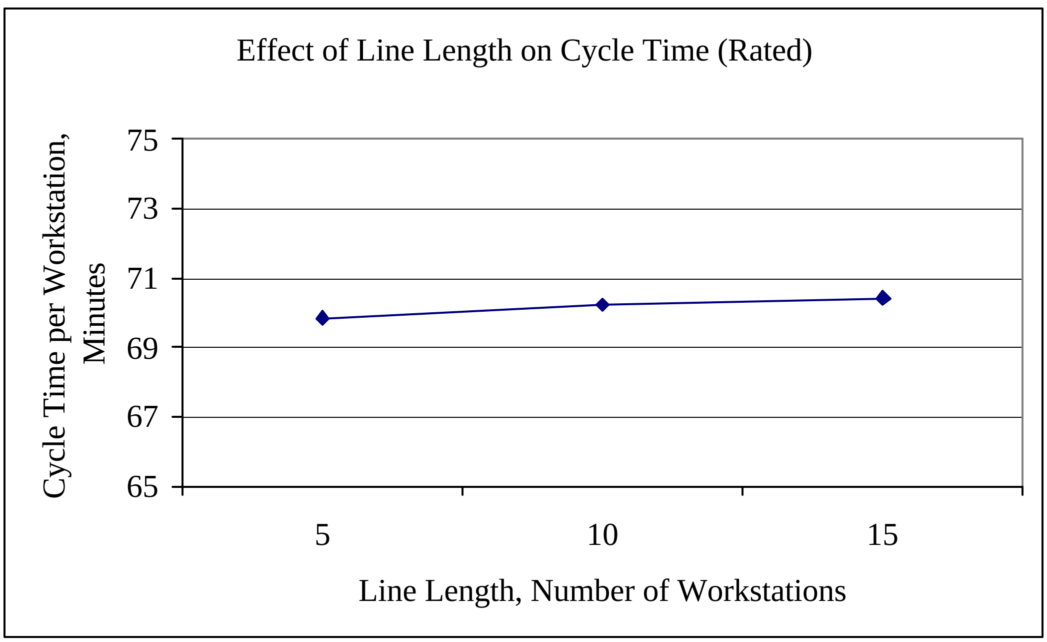

Figure 4. Effect of Line Length on Cycle Time (Rated)

Downtime

The increase from 0 to 10% downtime results in an increased cycle time of 13%. Increasing downtime to 30% increases cycle time an additional 37%, or 55% overall (see Figure 5). Interesting results will be seen when the interactions are discussed later.

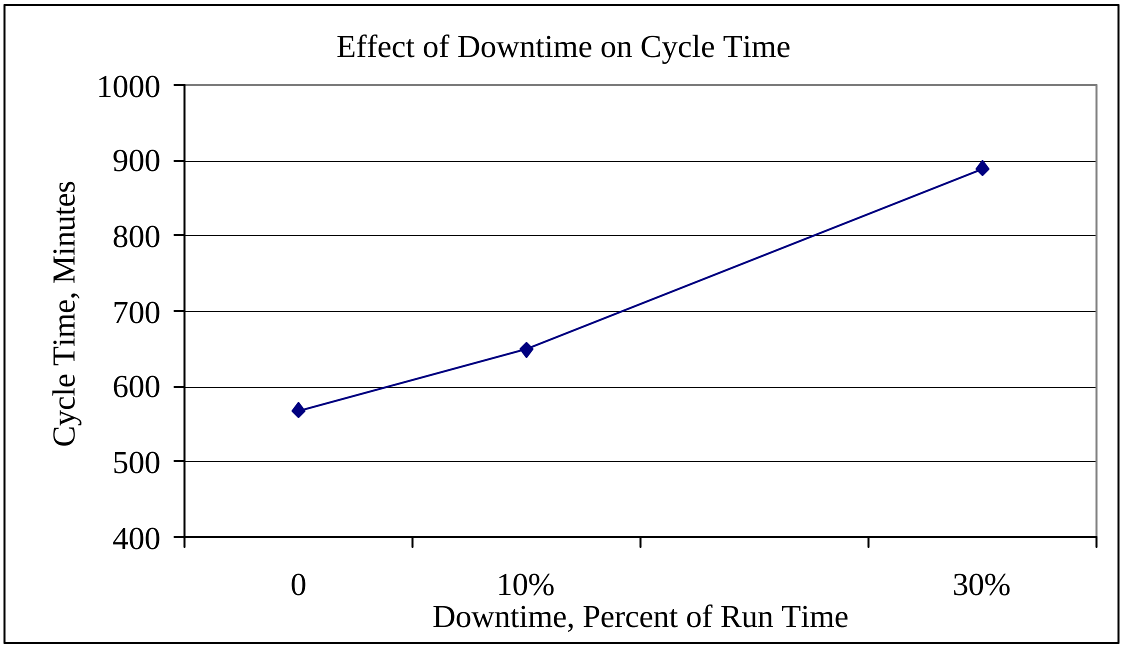

Figure 5. Effect of Downtime on Cycle Time

Protective Capacity

All scenarios including protective capacity reflect the same general shape as the protective capacity curve in Figure 6, with the largest effect occurring between 0 and 5%, and 5 and 10% protective capacity. As we will see later in the discussion, other factors influence the significance of the reduction in cycle time due to protective capacity.

Generally, the benefit of increasing protective capacity from 20% to 30% and from 30% to 40% is small and may not be economically rewarding.

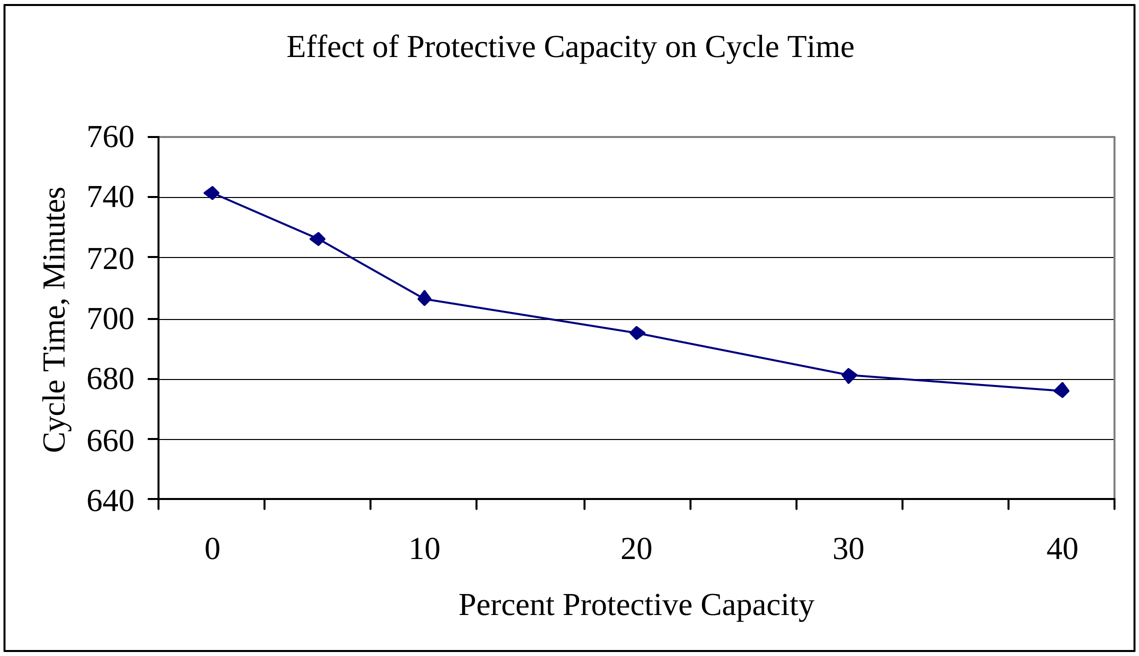

Figure 6. Effect of Protective Capacity on Cycle Time

Coefficient of Variation

The effect of increasing the process time variability of a serial production line is to increase the cycle time by 0.6%, 0.97%, and 3.8%, incrementally from 5% to 15% CV, from 15% to 25% CV, and 25% to 50% CV, respectively. The overall increase in cycle time due to increased variability from 5% to 50%, is 5.45%. Although this is not large numerically, the interaction of variability and other factors, as will be shown, can greatly influence production line performance. See Figure 7.

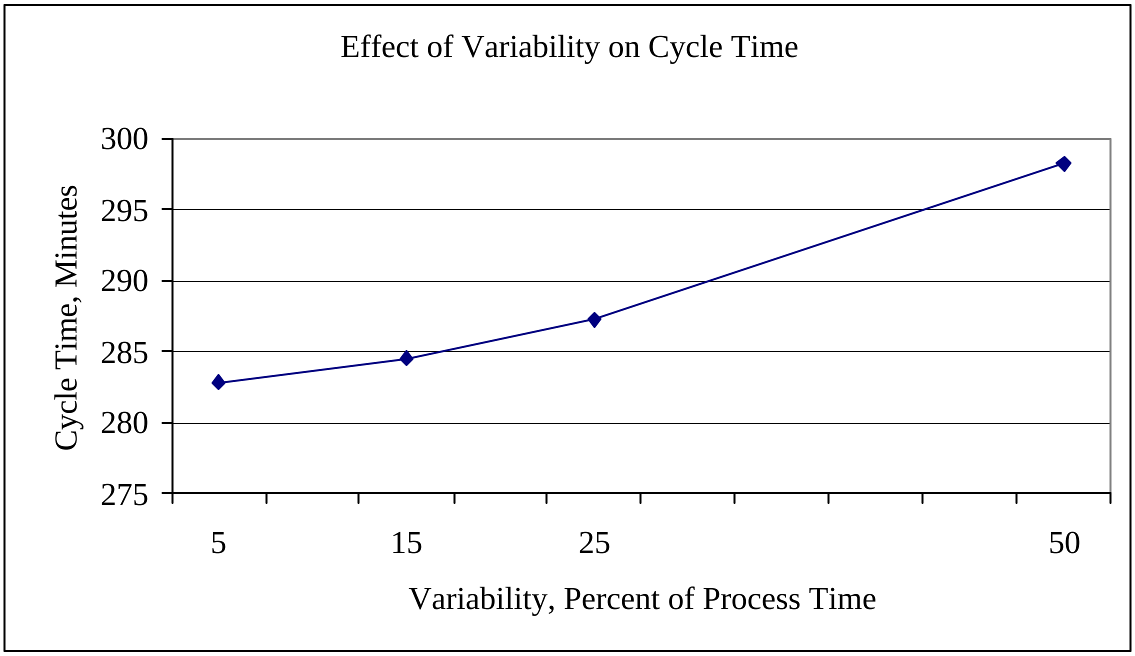

Figure 7. Effect of Variability on Cycle Time

Interactions

Protective Capacity Interactions

Figure 8 shows the effect of protective capacity with three levels of downtime. We can see that with 0% downtime there is no significant improvement in cycle time due to protective capacity. At 10% downtime, there is small incremental improvement (3.6, 1.5, 1.2, 0.6, and 0.25) percent respectively, and approximately 7% overall improvement in cycle time, most of which occurs near 5% protective capacity. At 30% downtime, protective capacity becomes more beneficial, reducing cycle time by 6.3% at 10% PC, 10.7% at 20% PC, 12.9% at 30% PC, and 14.2% (overall) at 40% PC. We see that with increasing downtime, protective capacity becomes more economically justifiable in terms of throughput.

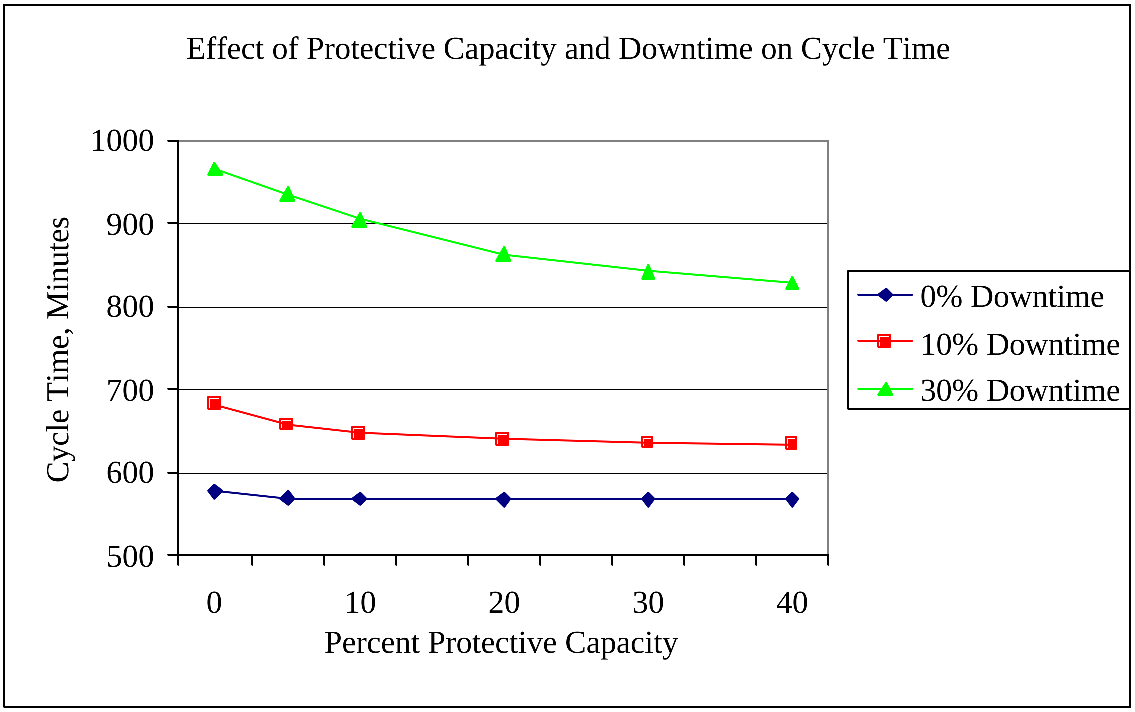

Figure 8. Effect of Protective Capacity and Downtime on Cycle Time

Figure 9 shows the effect of protective capacity with three levels of work-in-process. Although the higher WIP levels have longer cycle times, each scenario experiences a similar benefit from protective capacity, as illustrated by the similarly shaped curves. Likewise, the graphs for the interactions of protective capacity with variability, line length, and constraint location show that the presence of protective capacity reduces cycle time with approximately equal benefit across all levels of each factor. See Figures 10, 11, 12, and 13. Because the cycle time ranges for line length do not overlap, the average response was divided by the number of workstations in the line being modeled. Plotting this result (Figure 12) allows a better visualization of the similarity in the response variable across the levels of line length (number of workstations).

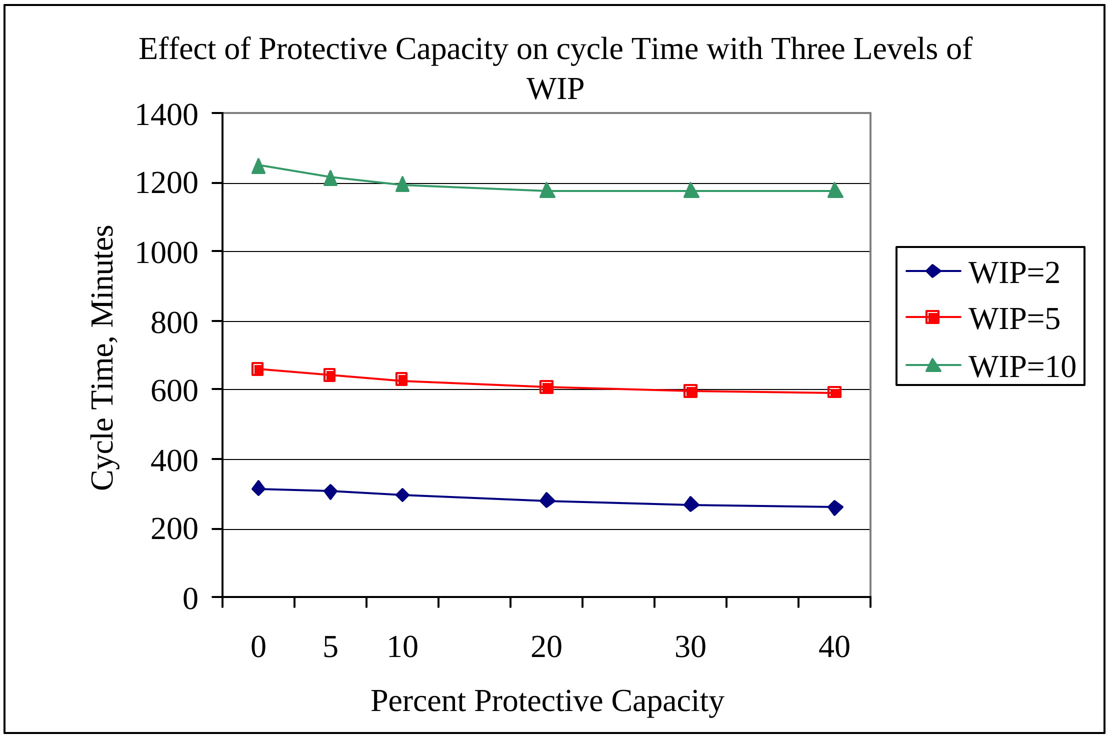

Figure 9. Effect of Protective Capacity and WIP on Cycle Time

When downtime, WIP, and protective capacity are observed for their combined effect on cycle time, as shown in Figure 14, we can observe that WIP has a greater influence on cycle time than downtime. Although with each increment of either downtime or WIP, cycle time increases, it is interesting to note that the sequence of cycle time increases follows the increase in WIP. We can observe that protective capacity has some benefit with all downtime values, regardless of the level of WIP. For the lowest level of WIP and DT simulated, there is a 2.6% decrease in CT with only 5% protective capacity, and only an additional 1.3% reduction from an additional 5% increase in PC.

Overall, this line design attained a cycle time reduction of 5.4% with 40% protective capacity. Interestingly, the line designs with higher WIP achieved smaller overall cycle time reductions from the presence of protective capacity. At 10% downtime, we can observe an increased benefit from the presence of protective capacity, showing an overall reduction in cycle time of 18.9% when WIP=2 units, and only 3.7% when WIP=10 units.

At 30% downtime, PC achieves a 22% cycle time reduction when WIP=2, 17% when WIP=5, and 10.4% when WIP=10. In all cases, there is measurable benefit from protective capacity. The significance of this benefit must be weighed against

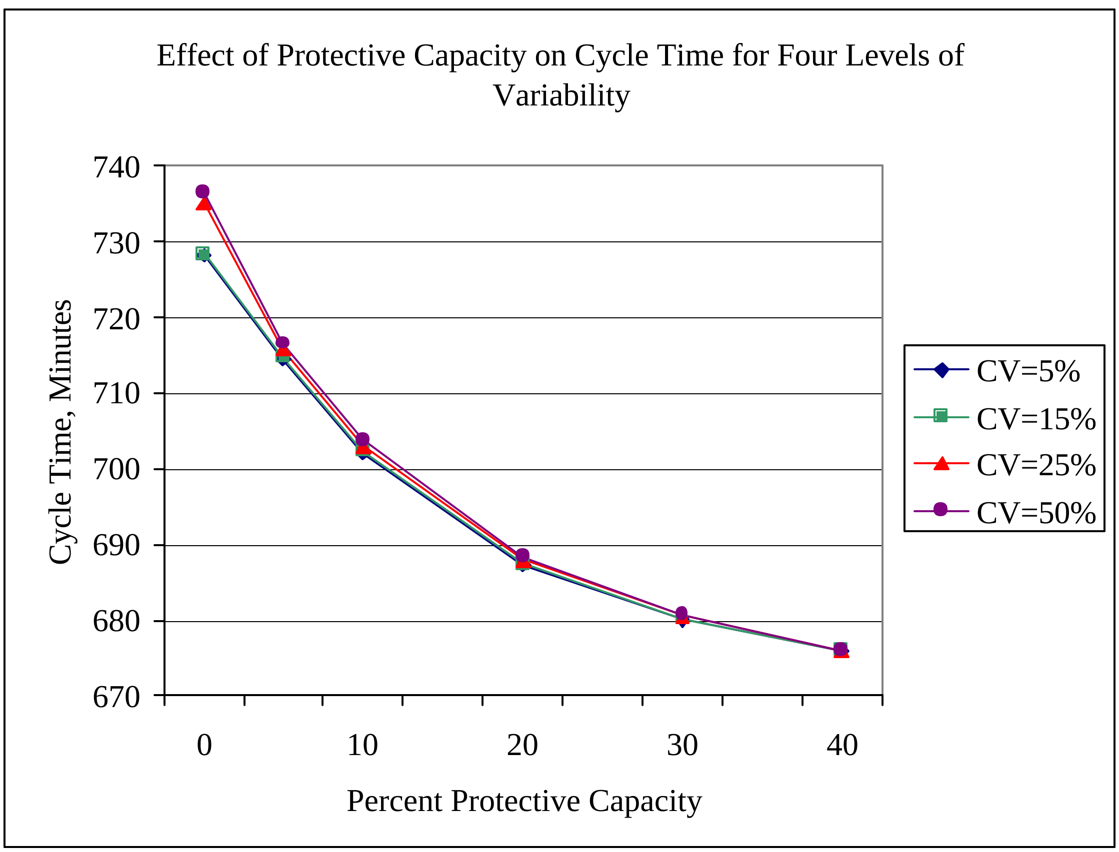

Figure 10. Effect of Protective Capacity and Variability on Cycle Time

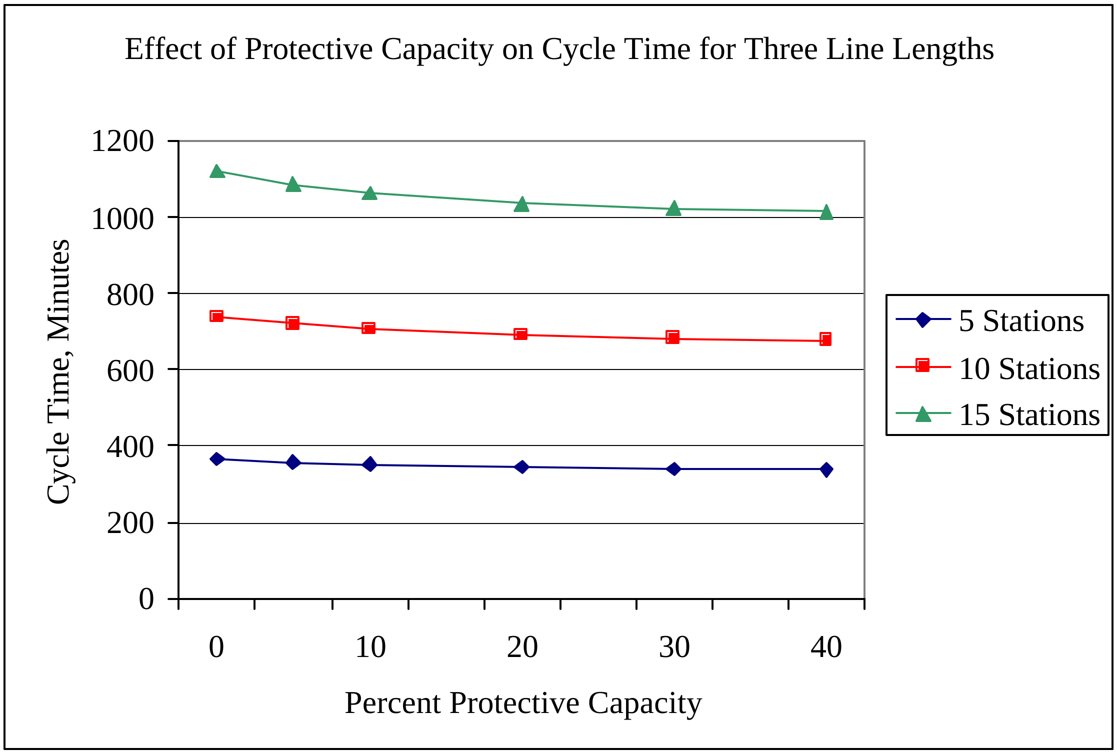

Figure 11. The Effect of Protective Capacity and Line Length on cycle Time

implementation costs and other factors, such as interruptions to current orders. From the interaction of downtime, line length, and protective capacity, a similar progression is evident from lowest to highest cycle time, with line length having more influence than downtime, as shown in Figure 15. We can observe that longer lines with greater downtime have more to gain from protective capacity than short lines with less downtime.

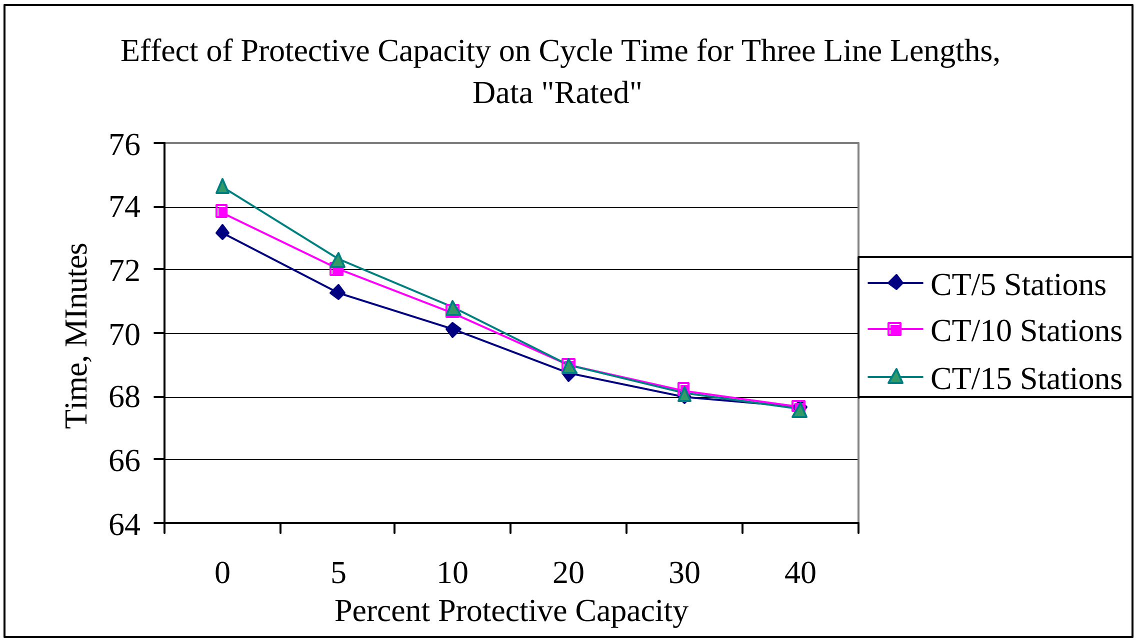

Figure 12. The Effect of Protective Capacity and Line Length on Cycle Time (Rated)

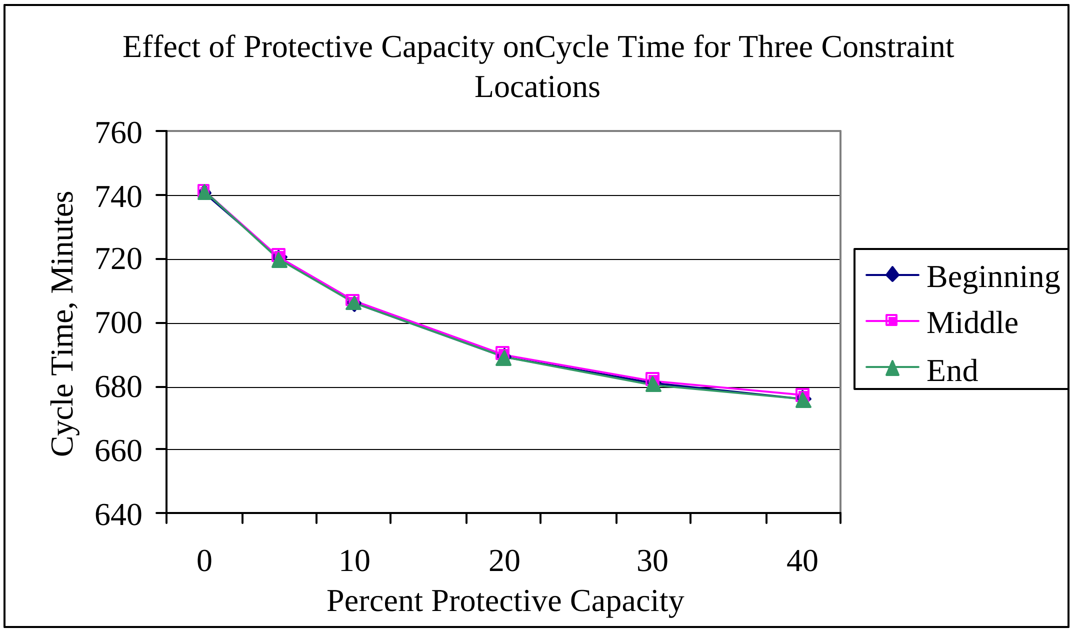

Figure 13. Effect of Protective Capacity and Constraint Location on Cycle Time

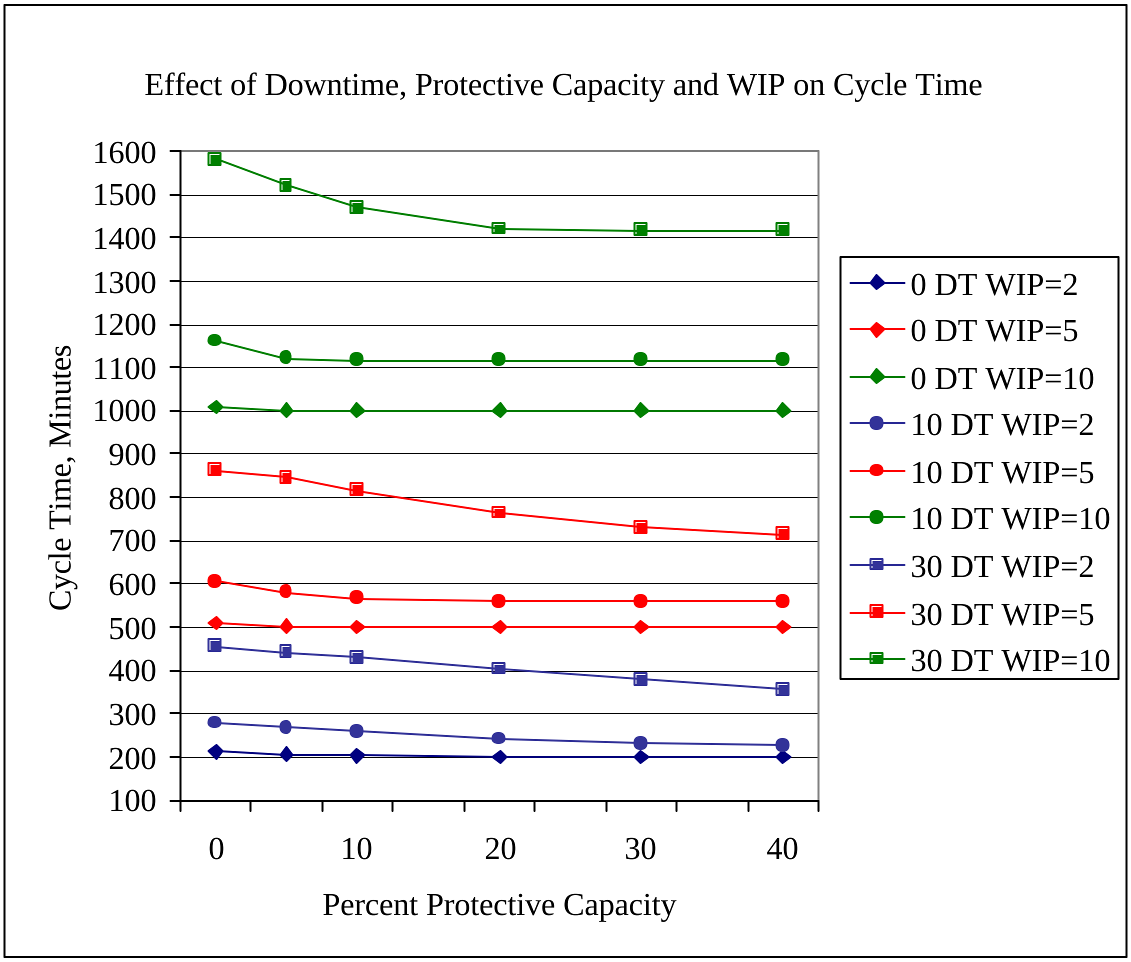

Figure 14. Effect of Downtime, PC, and WIP on Cycle Time

From Figure 16, we can see that WIP has a greater influence than variability on cycle times. The benefit for investing in protective capacity in lines with high variability is more apparent from Figures 17, 18, and 19. From these three graphs, we can observe that protective capacity has the ability to reduce cycle time in the presence of high variability to nearly the same level as that for lines with low variability, with the most

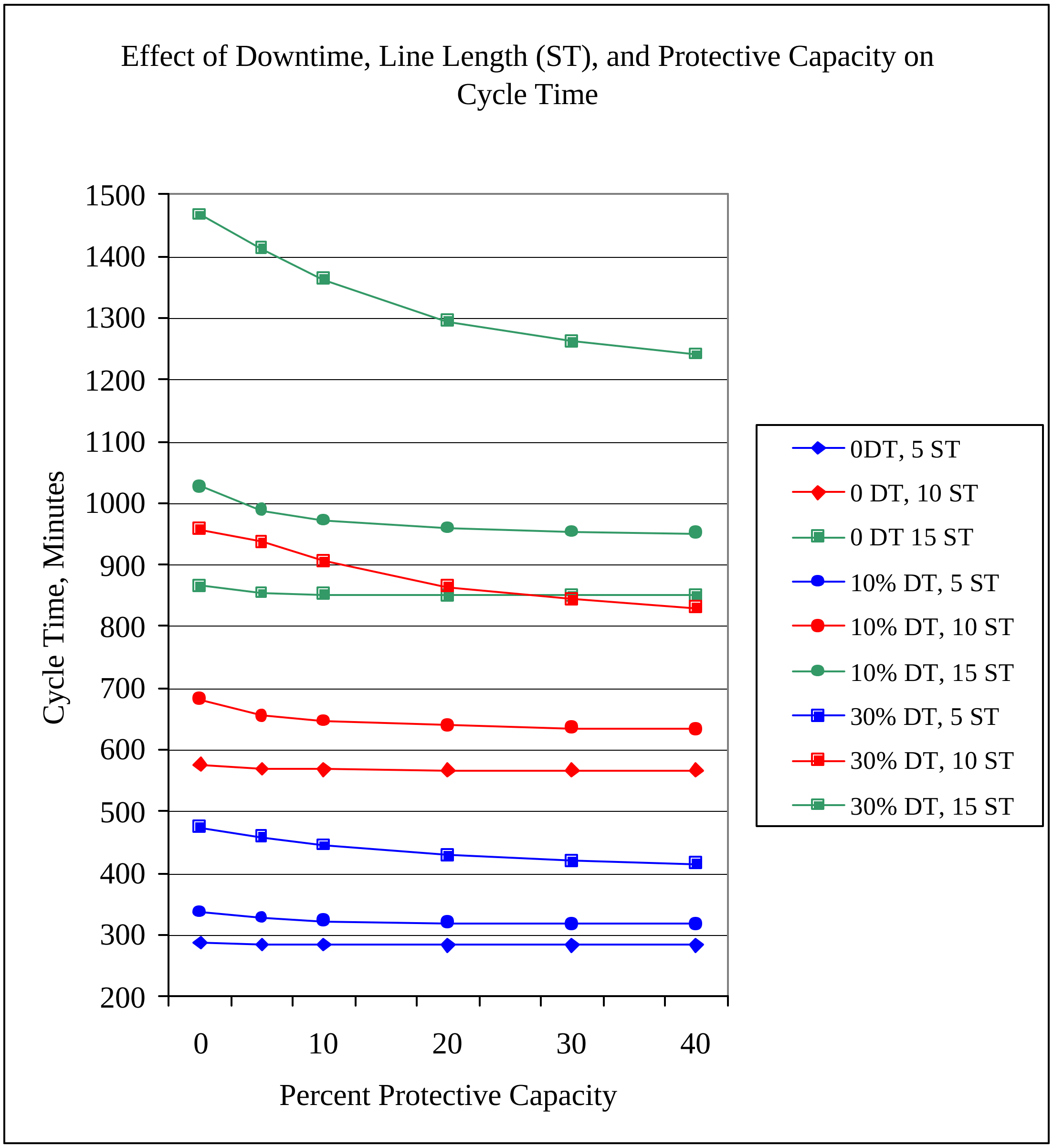

Figure 15. Effect of Downtime, Line Length, and Protective Capacity on Cycle Time

benefit occurring when WIP is low. Table 7 shows the increasing benefit of protective capacity as WIP is reduced. An existing production line experiencing high variability can be improved by an increase in capacity in non-constraint stations, or a reduction in WIP, resulting in a lower cycle time than another line with low variability and no or little protective capacity. Tradeoffs between improvement costs, demand, process capabilities and other factors will influence these decisions.

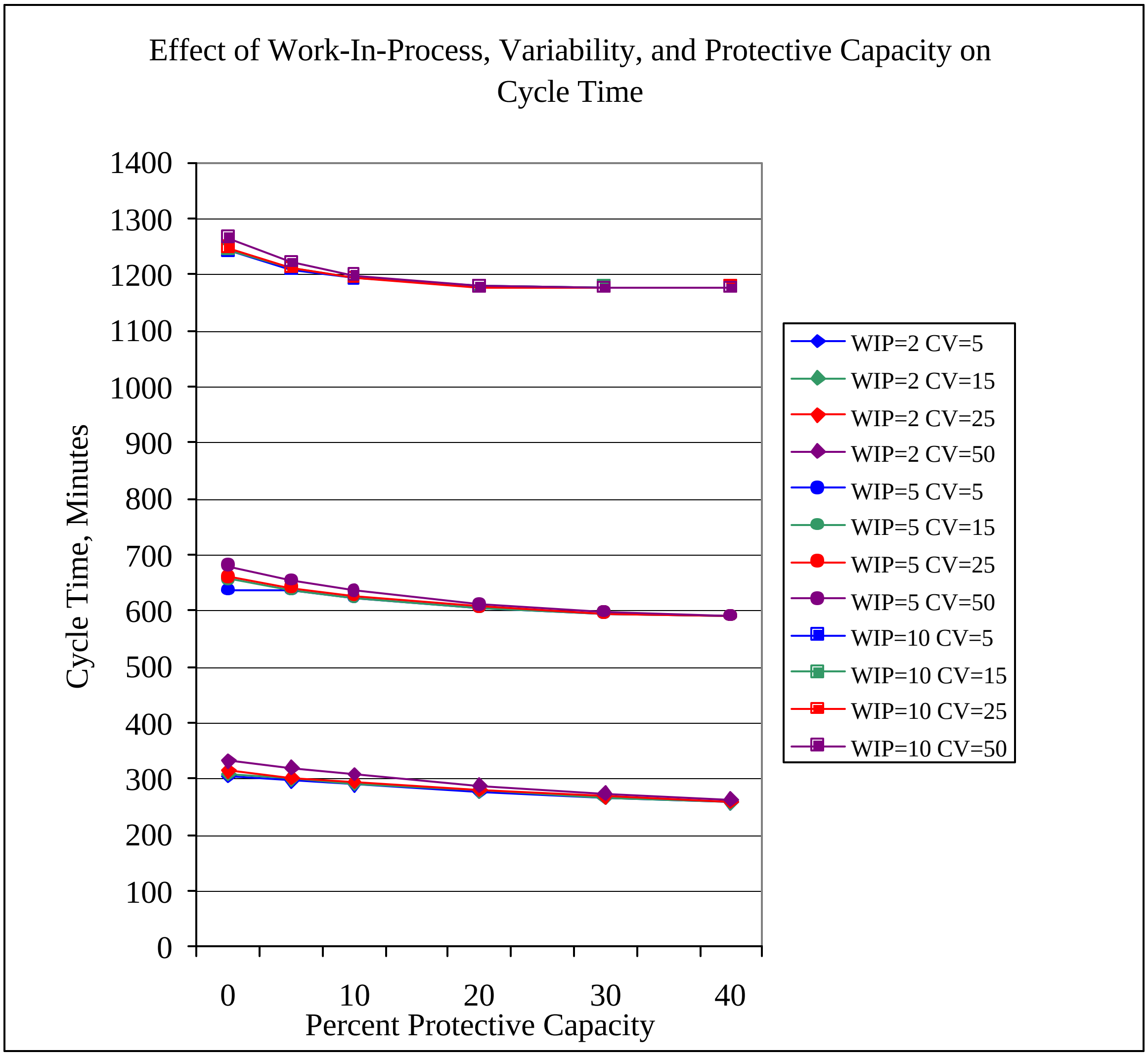

Figure 16. The Effect of PC, WIP, and Variability on Cycle Time

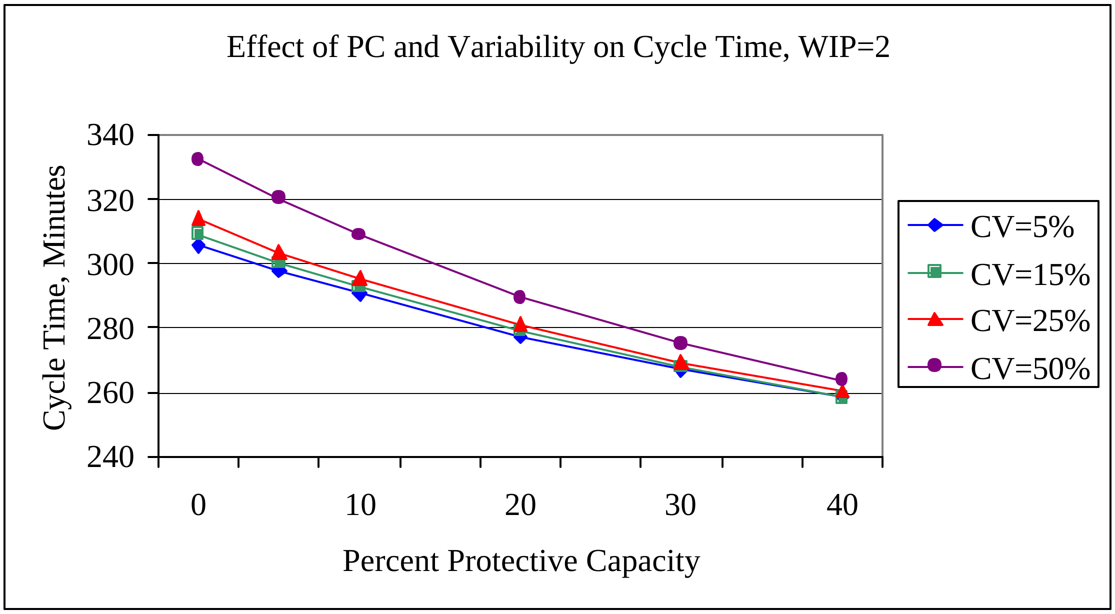

Figure 17. The Effect of PC and Variability on Cycle Time, WIP=2

Table 7. Cycle Time Reductions due to Protective Capacity as a Function of Variability and WIP

	% Cycle Time Reduction from 40% Protective Capacity		
Variability	WIP=2	WIP=5	WIP=10
5%	15.3	7.2	5.2
15%	16.4	9.9	5.3
25%	17.1	10.6	5.6
50%	20.6	13.1	7.1

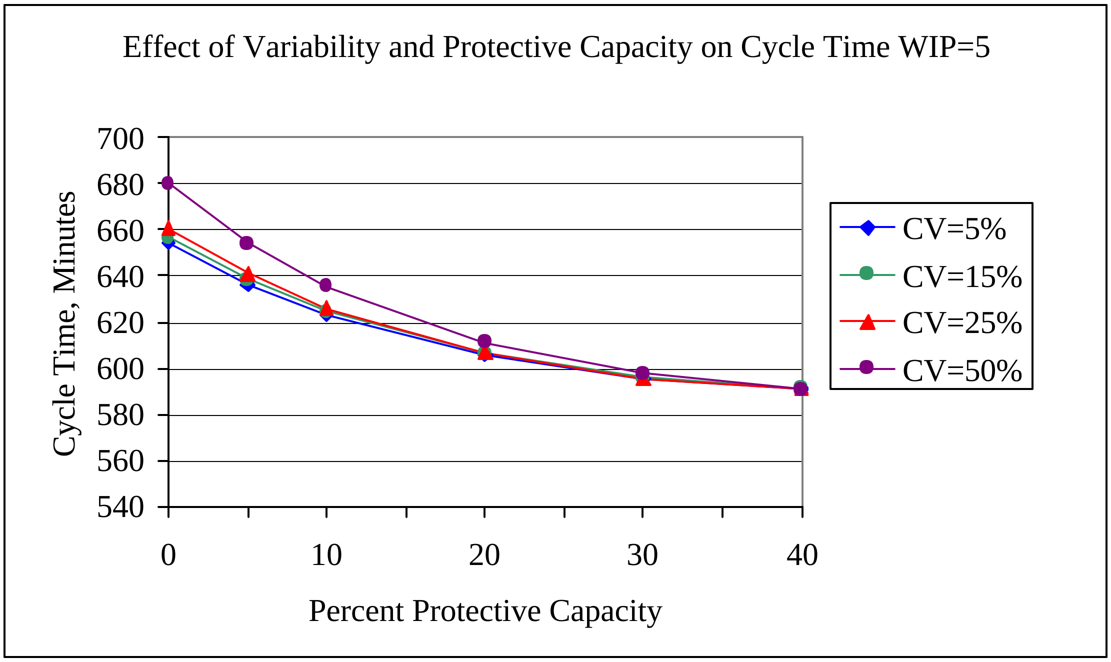

Figure 18. The Effect of PC and Variability on Cycle Time, WIP=5

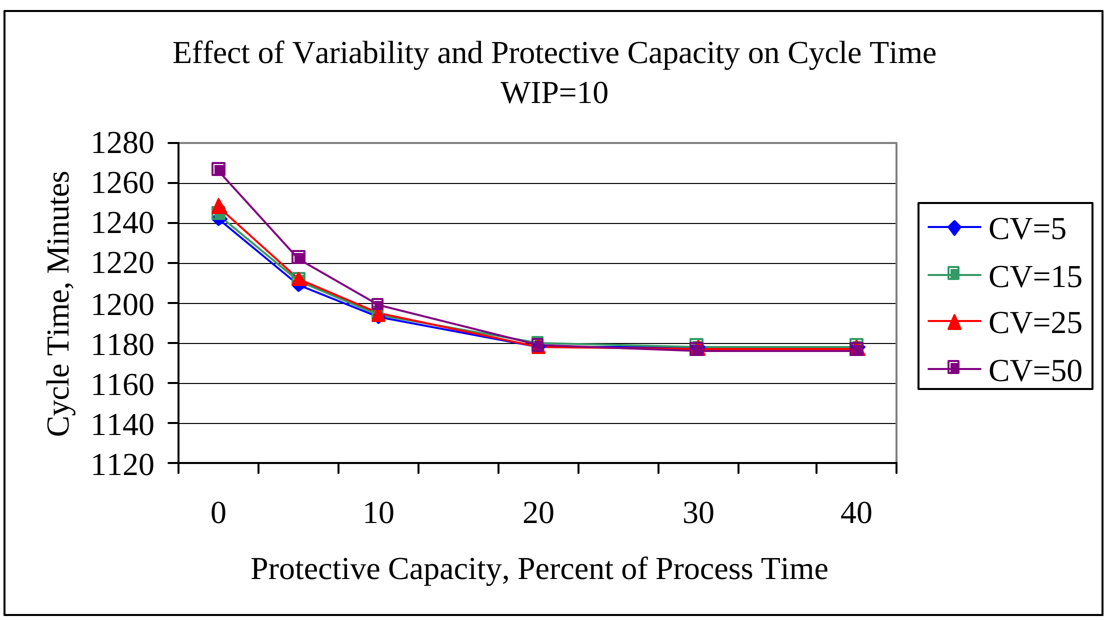

Figure 19. The Effect of PC and Variability on Cycle Time, WIP=10

Work-In-Process Interactions

When WIP and line length interact we see a more pronounced slope to the increasing cycle time due to WIP alone, see Figures 20 and 21, as compared to Figures 2 and 3. All three line lengths experience approximately the same effect from increased WIP. Increasing WIP from 2 units to 5 units of product per workstation, increases cycle time by about 110%. From 5 units to 10 units of product per workstation, cycle time increases by 93%, and the overall increase from 2 units to 10 units of product per workstation is over 300%.

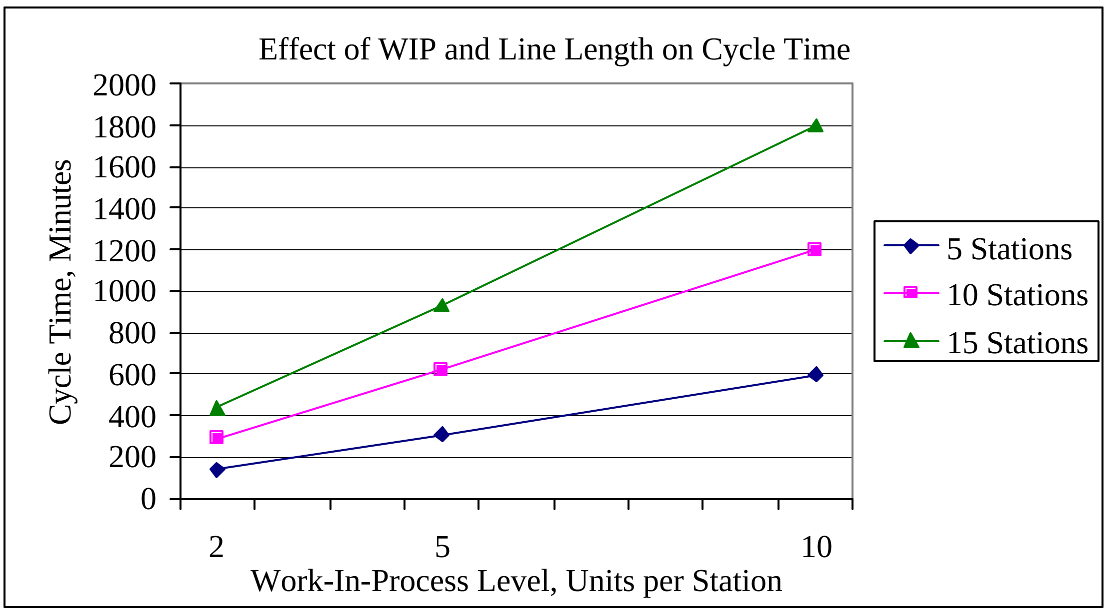

Figure 20. Effect of WIP and Line Length on Cycle Time, X=WIP

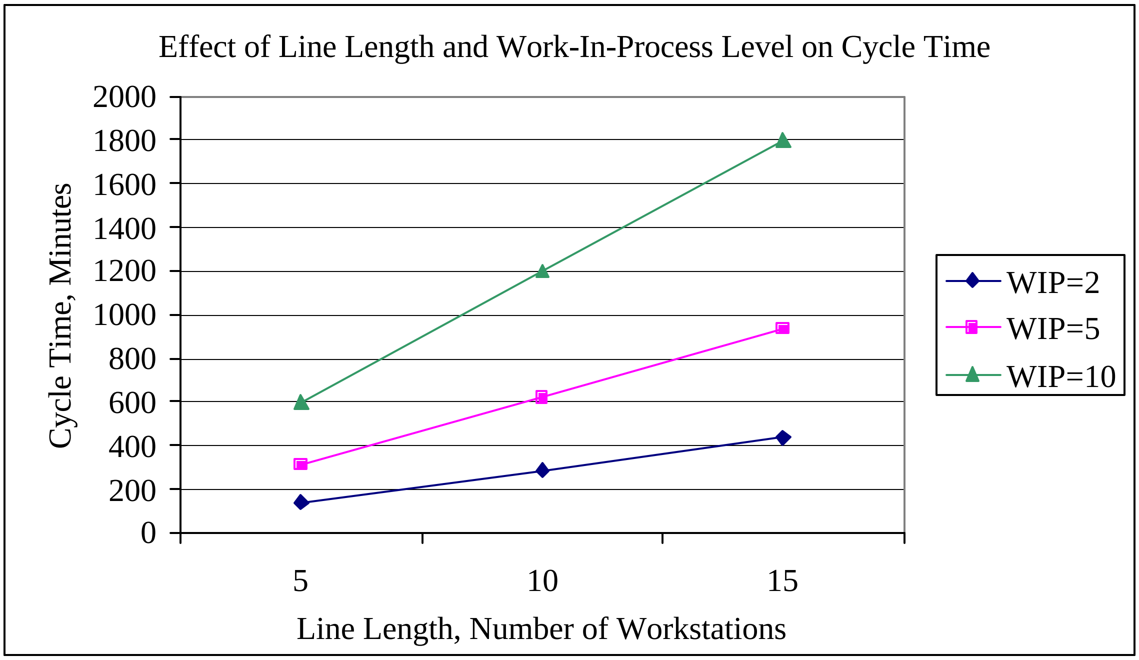

Figure 21. Effect of WIP and Line Length on Cycle Time, X=Line Length

From Figure 22 it is evident that increasing WIP from 2 units to 5 and from 5 units to 10 units per workstation increases cycle time by 146%, and 99% respectively, or 390% overall, for lines with no downtime. With only 10% downtime, cycle time increases 128% by increasing WIP to 5 units per station, and another 96% when WIP is increased to 10 units, or 350% overall. Lines with 30% downtime experience a 250% overall increase in cycle time due to increased WIP, 91% from 2 units to 5, and 89% from 5 units to 10. Figures 23 and 24 show that when WIP is low, variability has a greater impact, evidenced by a 5.4% increase in cycle time. For WIP=5, the cycle time increase is only 2.17%, and for WIP=10, cycle time increases only by 0.56%. This is not to say that cycle time does not increase, but only to say that the level of WIP influences the cycle time much more so than the variability, especially at higher levels of WIP.

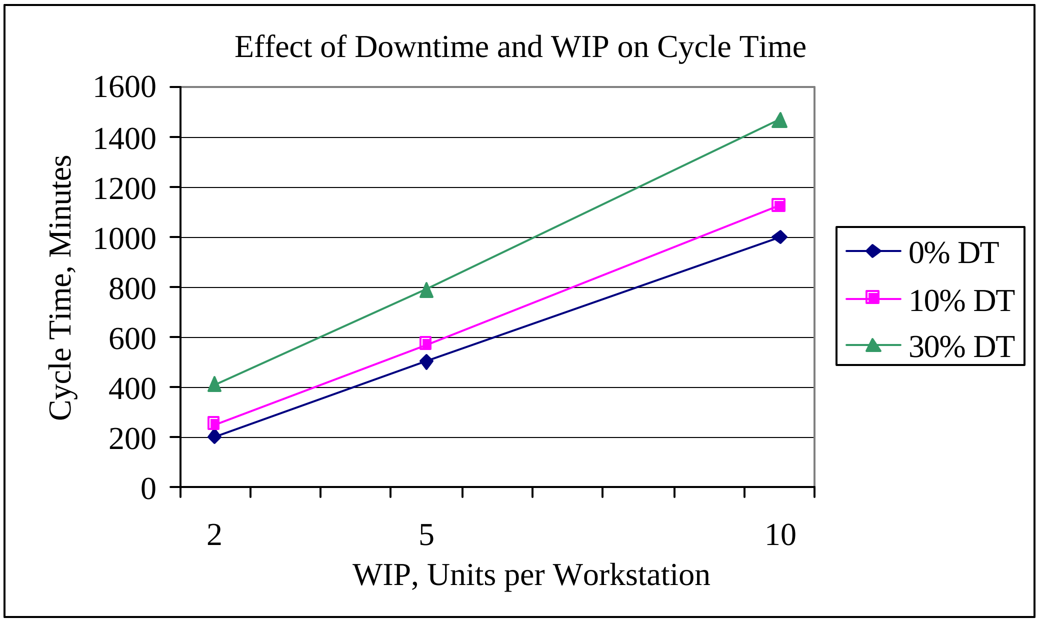

Figure 22. Effect of Downtime and WIP on Cycle Time

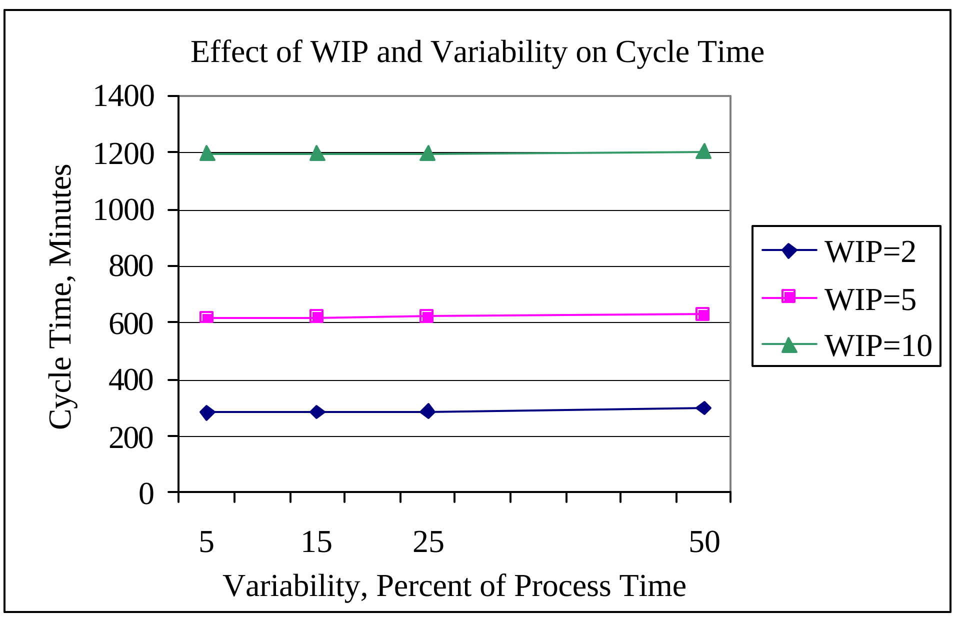

Figure 23. Effect of WIP and Variability on Cycle Time, X=CV

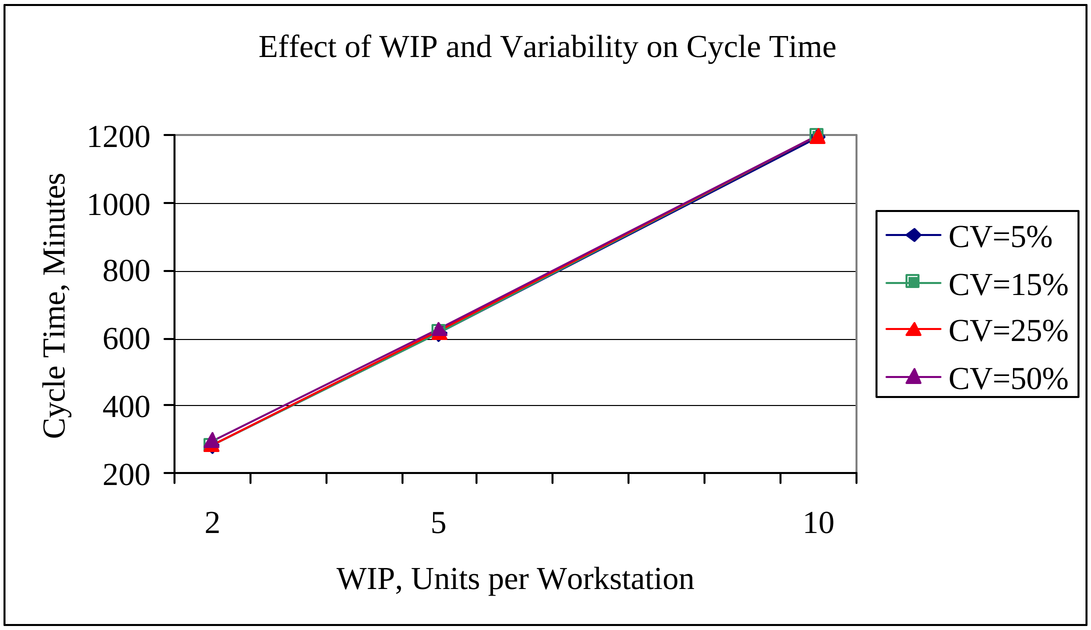

Figure 24. Effect of WIP and Variability on Cycle Time, X=WIP

Referring back to Figure 9 on page 30 shows the effect of protective capacity with three levels of WIP. As mentioned in the discussion on protective capacity, higher WIP levels have longer cycle times. Here we take a closer look at the effects of WIP in combination with protective capacity. When WIP is high, 20% protective capacity yields maximum cycle time reduction, with approximately 7% improvement. At 30% and 40% protective capacity there is no significant improvement in cycle time. For lines with less WIP, protective capacity continues to aid in cycle time reduction through the 40% level, although with diminishing incremental benefit. The higher the level of work-in-process, the less beneficial protective capacity is to reducing cycle time. Overall improvement is 7% when WIP=10, 10% for WIP=5, and 17% when WIP=2.

From Figure 25, the effect of the interaction of downtime, WIP, and line length, the three most significant individual factors in cycle time, can be observed. We can observe that all lines experienced an increase in cycle time due to increased WIP, line length, and downtime. As pointed out in the section on protective capacity interactions, WIP has a greater influence on cycle time than downtime. For lines with higher downtimes, less WIP would be desirable to reduce cycle times, however, more WIP is usually seen as desirable protection against downtime. Trade-offs must be made to take advantage of the better cycle times, weighing the cost of holding inventory against improvement costs to reduce downtimes. Remembering that WIP, followed by line length, followed by downtime influence cycle times can aid in these decisions.

As noted in the protective capacity interactions section in the discussion of Figure 14, with each increment of either downtime or WIP, cycle time increases, and the sequence of cycle time increases follows the increase in WIP. It has been shown that protective capacity has some benefit with all downtime values, regardless of the level of WIP. Referring again to Figures 18 and 19, shown in the protective capacity interactions section, we can make yet another observation about WIP levels in combination with variability. We can observe that the higher the level of WIP, the less beneficial protective capacity will be. This is evidenced by a decreasing percentage reduction in cycle time experienced by the lines with greater and greater amounts of work-in-process. The shading in Table 7 on page 38 illustrates the vertical and horizontal increase in protective capacity benefit as WIP decreases and variability increases.

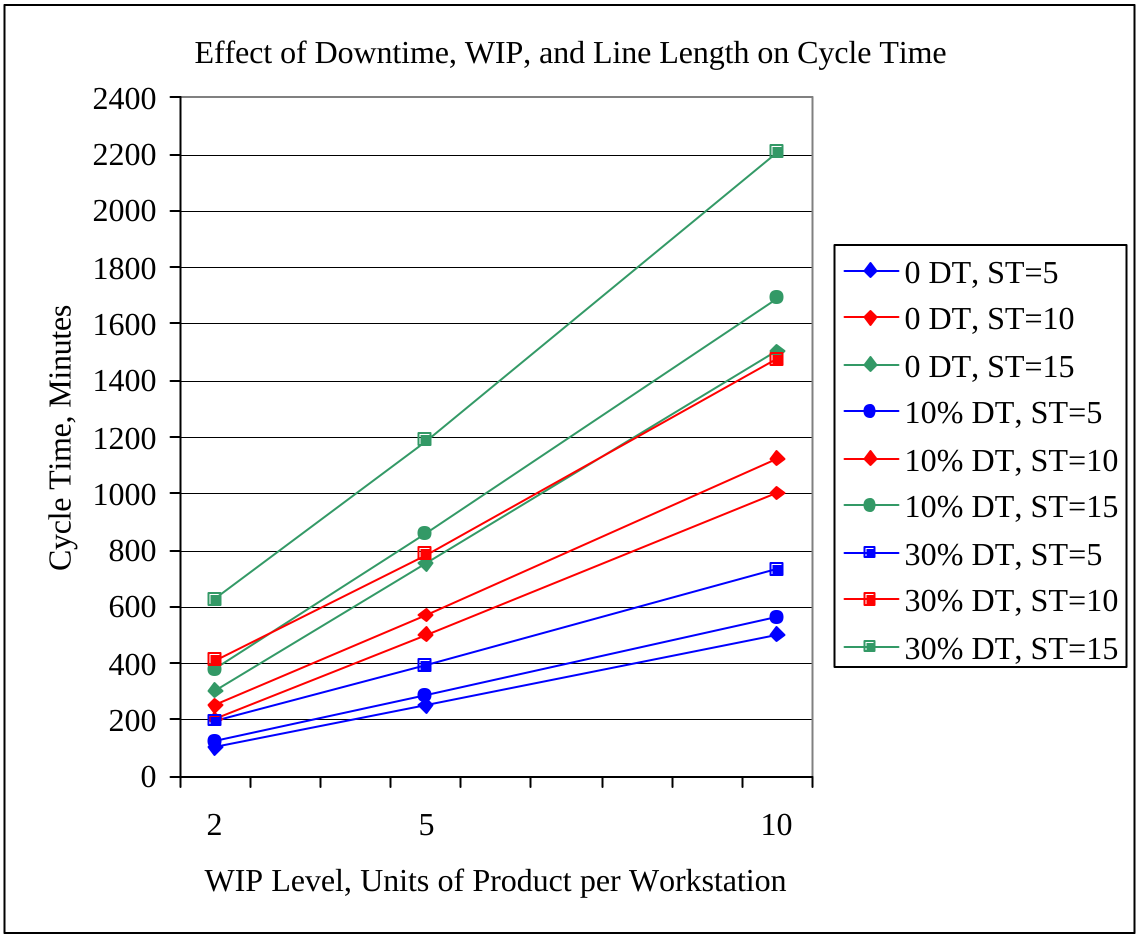

Figure 25. Effect of Downtime, WIP, and Line Length on Cycle Time

Line Length Interactions

Comparing Figure 26 to Figure 3 on page 25, it can be seen that downtime adds to the already increasing cycle time brought out by increasing the number of workstations, which we saw earlier. As discussed earlier, protective capacity reduces cycle time; in this interaction there is a progressively greater benefit as line length increases, shown in Figures 11 and 12, pages 32 and 33. The longer lines achieve a slightly greater reduction in cycle time due to protective capacity, as shown in Table 8, with the majority of the improvement occurring at 10 percent protective capacity.

Table 8. Three Line Lengths' Benefit from Protective Capacity

Line Length	5 Stations	10 Stations	15 Stations
% Cycle Time Reduction at 10% PC	4.19	4.28	5.14
Overall Cycle Time Reduction, %	4.58	4.87	5.68

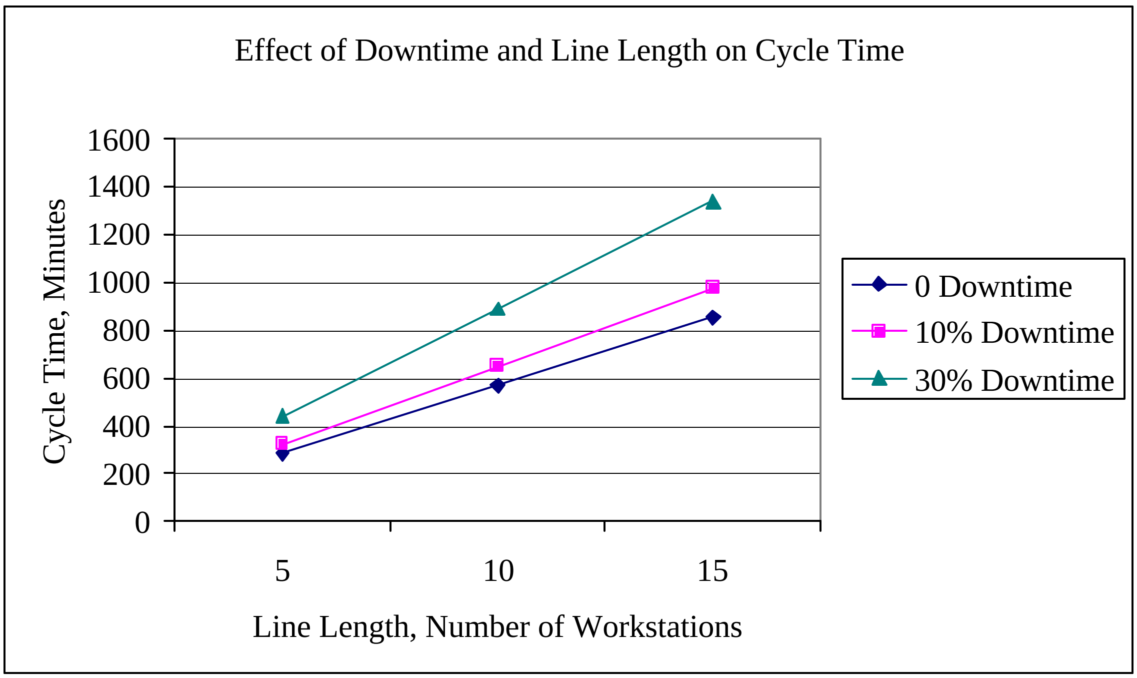

Figure 26. Effect of Downtime and Line Length on Cycle Time

In Figure 25, the effect of the interaction of downtime, WIP, and line length was illustrated. In addition to the comments mentioned in the WIP interactions section, it may also be beneficial to combine two or more workstations into a single process, thus reducing line length, which would also contribute to reduced cycle times. Figure 15 shows the combined effects of downtime, line length, and protective capacity, and was discussed earlier, in the section "Protective Capacity Interactions." Briefly, long lines have the highest cycle times in these interactions.

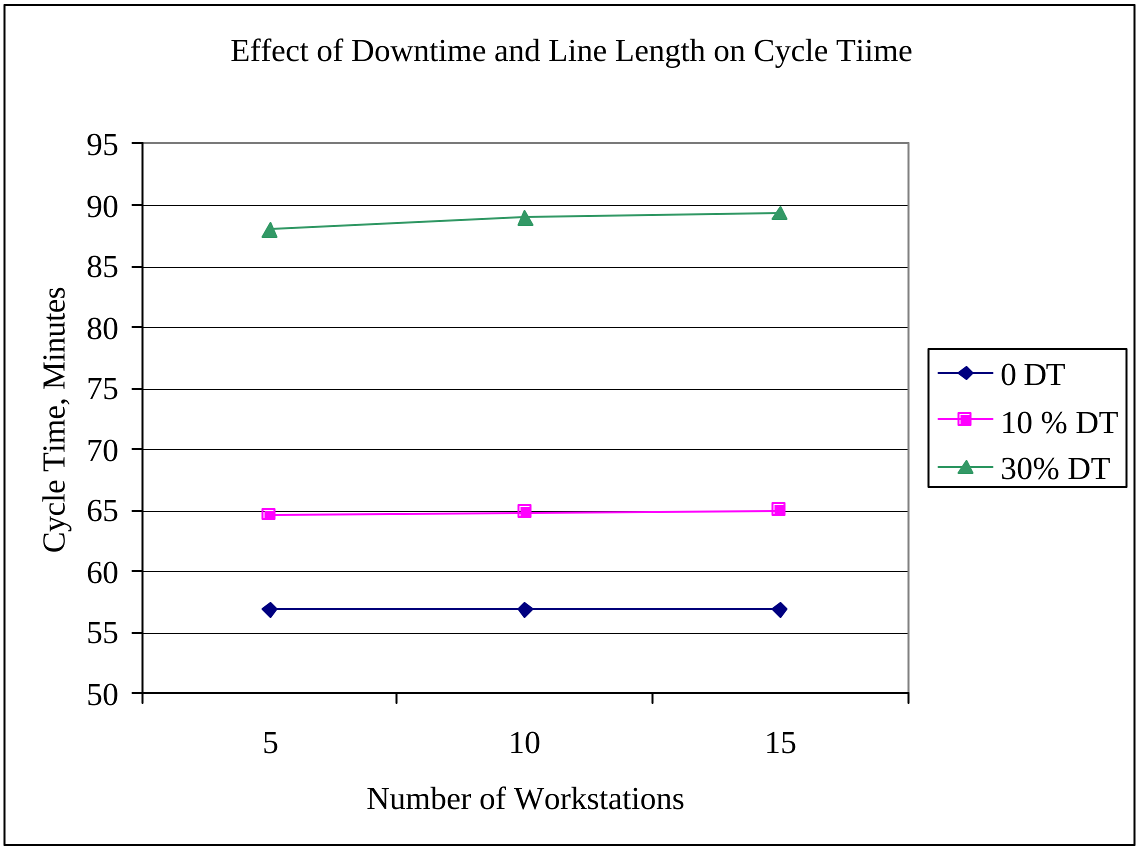

Figure 27. Effect of Downtime and Line Length on Cycle Time, Rated per Workstation

Downtime Interactions

The downtime interactions have been discussed in the preceding sections; highlights are mentioned here.

Figure 22 showed that work-in-process is more influential than downtime and that the greater the downtime, the lower (proportionally) the overall increase in cycle time. Figure 8 showed that the greater the downtime, the greater the benefit of investments in protective capacity. Figure 14 showed that increasing WIP levels are more influential than increasing downtime levels. It was also observed that longer lines with greater downtime have more to gain from protective capacity than short lines with less DT.

Variability Interactions

Referred to in this paper as variability, or CV, this factor had a lesser impact on the response of cycle time than the other factors discussed thus far. Hopp and Spearman classify coefficients of variation less than 0.75 as “low variability,” suitable for process times without outages. According to Hopp and Spearman 0.75 = CV <1.33 is considered “moderate variability”, and CV = 1.33 is considered “high variability” [7]. It is not as surprising, then that variability alone, in the ranges studied here, does not have as strong an impact as variability in combination with other factors. The interdependencies and statistical fluctuations were expected to become evident in increased response times, when interacting factors were introduced to the model, and they did. The most significant variability interactions are those in combination with WIP and protective capacity. As previously discussed, Figure 7 illustrates that lines with higher process time variability have longer cycle times.

From Figure 16 as discussed earlier, it was shown that WIP has a greater influence than variability on cycle times. It has also been shown that protective capacity has the ability to reduce cycle time in the presence of high variability to the same level as that for lines with low variability, with the most benefit occurring when WIP is low.

Regression Summary

Multiple Linear Regression (stepwise), utilizing the five numerical main effects, ten two-way interactions, and five squared main effects, was also used to analyze the simulation data. The regression output report is shown in Table 9. The interactions and squared main effects are represented as factors X1 through X15, listed in Table 10, and are considered by the SAS program to be other regressor variables. A scatter plot of standard error residuals, along with a residual histogram of occurrences substantiate that the errors are approximately normally distributed. The regression coefficients developed are shown in Table 10. Of the 20 factors entered, three main effects, all ten 2-way interactions, and two squared main effects are included in the approximating equation. The resulting Coefficient of Determination (R^2) for the model is 0.99691.

The all-possible regression method was also run, yielding a model containing all 20 regressors, with an R^2 value of 0.99754, which was also obtained by the MLR when all regressors were included in the model statement. The simpler model with 16 terms was chosen as a good approximation with an R^2 loss of only 0.00063, accounting for only 0.063% of the variability, caused by the absence of 5 regressors. The resulting equation can be utilized to predict cycle time for varying values of each factor, within the ranges of the experimental variables, which are given in Table 11.

The resulting regression equation is:

$$\underline{CT}=55.07330396 -4.75656376*\underline{DT}-13.31263293*\underline{WIP}-6.04734206*\underline{ST}+1.10722045*\underline{DT}*\underline{WIP}+0.56960974*\underline{DT}*\underline{CV}+1.12384676*\underline{DT}*\underline{ST}-0.11303788*\underline{DT}*\underline{PC}-2.36951007*\underline{WIP}*\underline{CV}+11.33724632*\underline{WIP}*\underline{ST}-0.01628162*\underline{WIP}*\underline{PC}+2.75701659*\underline{CV}*\underline{ST}-1.20487627*\underline{CV}*\underline{PC}-0.18022994*\underline{ST}*\underline{PC}+42.63762603*\underline{CV}^2 +0.05315411*\underline{PC}^2. \qquad \text{(Equation 2)}$$

From this model we can predict the resulting cycle time for a serial production line with values of the factors studied, within the specified ranges. With this design aid, perhaps the predicted throughput can be more dependably realized on the production floor. Additionally, for existing flow lines, Equation 2 can be employed to predict the outcomes of various process improvements prior to implementation, enabling the estimation of possible benefits. These outcomes can then be weighed against the costs of each alternative improvement, and trade-off decisions can be made. It remains to test the resulting regression model in actual practice.

Table 9. SAS Regression Results

The SAS System 08:13 Friday, September 14, 2001 34

Step15 Variable X7 Entered R-square = 0.99691297 C(p) = 19.47004522

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	15	5307349121.1582	353823274.74388	418180	0.0001
Error	19424	16434683.404360	846.10190508		
Total	19439	5323783804.5626			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	55.07330396	1.46889888	1189381.3797478	1405.72	0.0001
DT	-4.75656376	0.06119665	5111566.7392420	6041.31	0.0001
WIP	-13.31263293	0.21330382	3295742.8810664	3895.21	0.0001
ST	-6.04734206	0.14428507	1486308.4609390	1756.65	0.0001
X1	1.10722045	0.00506908	40367607.932699	47710.1	0.0001
X2	0.56960974	0.09822407	28453.89082587	33.63	0.0001
X3	1.12384676	0.00409729	63656721.646888	75235.3	0.0001
X4	-0.11303788	0.00116305	7992390.3033604	9446.13	0.0001
X5	-2.36951007	0.36027048	36600.11424187	43.26	0.0001
X6	11.33724632	0.01548629	453464239.53847	535945	0.0001
X7	-0.01628162	0.00423530	12504.00467447	14.78	0.0001
X8	2.75701659	0.27555577	84699.80672156	100.11	0.0001
X9	-1.20487627	0.08330944	176977.93892983	209.17	0.0001
X10	-0.18022994	0.00319288	2695949.8994856	3186.32	0.0001
X13	42.63762603	6.03081193	42291.89393780	49.98	0.0001
X15	0.05315411	0.00095802	2604638.3450266	3078.40	0.0001

Bounds on condition number: 13.38488, 1602.675

All variables left in the model are significant at the 0.0100 level.
No other variable met the 0.0100 significance level for entry into the model.

Table 10. Regressor Coefficients

Factor	Interaction Represented	Coefficient
X1	DT and WIP	1.10722045
X2	DT and CV	0.56960974
X3	DT and ST	1.12384676
X4	DT and PC	-0.11303788
X5	WIP and CV	-2.36951007
X6	WIP and ST	11.33724632
X7	WIP and PC	-0.01628162
X8	CV and St	2.75701659
X9	CV and PC	-1.20487627
X10	ST and PC	-0.18022994
X11	DT^2	0
X12	WIP^2	0
X13	CV^2	42.63762603
X14	ST^2	0
X15	PC^2	0.05315411

Table 11. Relevant Range of Regression Model

Variable	Low	High
Downtime	0%	30%
Work-In-Progress	2 Units per Workstation (WIP=10 for 5-station line)	10 Units per Workstation (WIP=150 for 15-station line)
Coefficient of Variability	0.05	0.50
Line Length (Number of Workstations)	5	15
Protective Capacity	0	40%
Constraint Location	First Station	Last Station

CHAPTER V

SUMMARY AND CONCLUSIONS

A main contribution of this research is the extension of previous protective capacity studies to longer lines. The results indicate that protective capacity can positively affect cycle times in most situations. Specifically, generalizations deduced from the analysis pertaining to each of the research questions asked on page 15 are listed below.

1. Do longer lines (with more workstations) require more protective capacity than shorter lines?

   Yes:

   - Line length is the second most significant factor affecting cycle time.
   - Protective capacity does have the ability to reduce cycle time of a long line to the cycle time for a shorter line without protective capacity.
   - Long lines obtain most of their reduction in cycle time from 10% protective capacity.
   - For the interaction of downtime, line length, and protective capacity, long lines have the highest cycle times.
   - When lines are short, downtime is low, and WIP is low to moderate, protective capacity may not "buy" much improvement in cycle time.

2. For what conditions does cycle time benefit from the presence of protective capacity?

    - ❖ The greater the downtime, the greater the cycle time improvement from protective capacity.
    - ❖ When WIP is high, downtime is high, variability is high, and there are several stations in the line, protective capacity can have a significant beneficial effect on cycle time.
    - ❖ Where there is low variability, low downtime, and low WIP, protective capacity does not contribute significantly to reduced cycle times.
    - ❖ In the CONWIP line designs studied, constraint location was not significantly influential in affecting cycle times.
    - ❖ Cycle time reductions from protective capacity increase with each increase in protective capacity; however, most of the protective capacity benefit is obtained by 30% PC.
    - ❖ In many cases a significant improvement in cycle time can be obtained with as little as 5% or 10% protective capacity.

3. Does the level of Work-in-process affect protective capacity's ability to obtain improved cycle times?

    Yes:

    - ❖ The higher the level of work-in-process, the lower the benefit from protective capacity.

- ❖ Work-in-process levels, followed by line length, followed by downtime are the most significant factors affecting cycle time.

4. Is there a numerical relationship between serial line operating conditions and the level of protective capacity needed for reduced cycle time?

   Yes:

   - ❖ A second main contribution of this research is the estimation of a numerical relationship between serial production line variables and cycle time. See Equation 2 on page 49. The regression model can be used to estimate the benefit or loss of proposed changes to existing production lines, as well as to estimate the outcome of proposed lines.

Areas For Further Research

A possible extension of this research is to investigate the impact of the various variables with progressive protective capacity, that is, each workstation having successively more excess capacity than the previous station, leading away from the constraint. (This study was conducted with all workstations having the same level of excess capacity.) The studies performed by Atwater and Chakravorty used a successively increasing processing speed, stating that it represented approximately 18% protective capacity. Another extension would be to repeat this study using a normal distribution for processing times, as indicated by Hopp and Spearman's recent book, Factory Physics [7].

The regression equation needs to be tested in actual practice. To evaluate existing production lines in need of improvement, test options with the regression model developed herein, and compare to actual outcomes, could lead to cost and time savings for process engineers and manufacturing facilities.

Another study could be conducted without maintaining constant work-in-process, using a distribution for arrivals. An additional study could be done with the total process time remaining unchanged, with the number of workstations varied. Line length effects may possibly be more clearly observed in this manner. It would also be interesting to contrast these CONWIP results with scenarios having a specific Kanban size, since large queues are not always practical.

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APPENDIX

DETAILS OF THE SIMULATION MODEL

Details of the Simulation Model

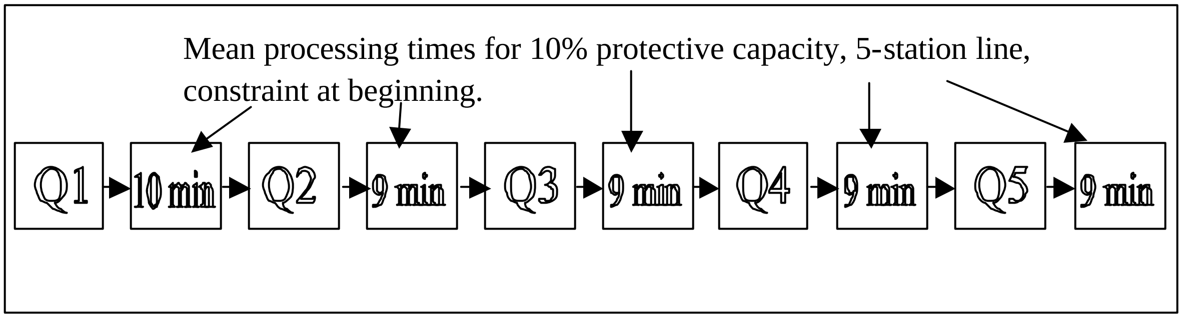

Figure 28. Example Simulation Model Layout Details

Table 12. Lognormal Process Time Distribution Parameters

Protective Capacity	Mean Processing Time	Standard Deviation of Processing Time
0%	10 Minutes	10 x CV
5%	9.5 Minutes	9.5 x CV
10%	9 Minutes	9 x CV
20%	8 Minutes	8 x CV
30%	7 Minutes	7 x CV
40%	6 Minutes	6 x CV

Table 13. Downtime Distributions

<table>
<tr><th>10% Downtime Frequency</th><th>10% Downtime Duration</th><th>30% Downtime Frequency</th><th>30% Downtime Duration</th></tr>
<tr><td>Exp (270)</td><td>Lognormal(30,9)</td><td>Exp(117)</td><td>Lognormal(42,13)</td></tr>
<tr><td colspan="2">Downtime System
MTBF = 270 and MTTR=30
30/(30+270)=0.10</td><td colspan="2">Downtime System
MTBF = 117 and MTTR=50
50/(50+117)=0.30 This setting resulted in 37% downtime, so parameters were adjusted to obtain 30% downtime L(42,13) yields 29.98-30.12% DT</td></tr>
</table>

Table 14. Workstation WIP Levels and Initial Conditions

No. of workstations	WIP per station	Total Line WIP	Initial Condition
5	2	10	2 units in each queue
5	5	25	5 units in each queue
5	10	50	10 units in each queue
10	2	20	2 units in each queue
10	5	50	5 units in each queue
10	10	100	10 units in each queue
15	2	30	2 units in each queue
15	5	75	5 units in each queue
15	10	150	10 units in each queue

Assumptions:

1. Tests are run on dedicated lines, no changeovers.
2. Non-constraint workstations have equal level of protective capacity.
3. Repair times begin when downtime occurs with no waiting.
4. Worst-case scenario has longest transient period; this time period is used for transient in all scenarios run.
5. Lognormal distribution describes repair times as shown in references 18, 19, 20.
6. CONWIP operating system; as an entity exits the system, another entity enters the system at queue 1.

Replications Calculations

$$i \geq S^2(n)\left[\frac{Z_{(1-a\ /\ 2)}}{g'\bar{x}(n)}\right]^2 \qquad \text{Equation (1)}$$

where α= 0.01, and γ'= 0.047619, s(n) and x(n) are taken from the sample run of 10 replications of the worst-case scenario (n=10).

S=62.9968 (sample standard deviation) $\bar{x}(n)$ =1752.2867 minutes

For α= 0.05 $Z_{(1-\alpha/2)}$=1.96 These figures result in i = 2.1896

For α= 0.01 $Z_{(1-\alpha/2)}$=2.58 These figures result in i = 3.79

For α= 0.01 $t_{(9,1-\alpha/2)}$=3.25 These figures result in i = 6.0205