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Design Of The Layout Of A Manufacturing Facility With A Closed Loop Conveyor With Shortcuts Using Queueing Theory And Genetic Algorithms

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DESIGN OF THE LAYOUT OF A MANUFACTURING FACILITY WITH A CLOSED LOOP CONVEYOR WITH SHORTCUTS USING QUEUEING THEORY AND GENETIC ALGORITHMS

by

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ABSTRACT

With the ongoing technology battles and price wars in today's competitive economy, every company is looking for an advantage over its peers. A particular choice of facility layout can have a significant impact on the ability of a company to maintain lower operational expenses under uncertain economic conditions. It is known that systems with less congestion have lower operational costs. Traditionally, manufacturing facility layout problem methods aim at minimizing the total distance traveled, the material handling cost, or the time in the system (based on distance traveled at a specific speed).

The proposed methodology solves the looped layout design problem for a looped layout manufacturing facility with a looped conveyor material handling system with shortcuts using a system performance metric, i.e. the work in process (WIP) on the conveyor and at the input stations to the conveyor, as a factor in the minimizing function for the facility layout optimization problem which is solved heuristically using a permutation genetic algorithm. The proposed methodology also presents the case for determining the shortcut locations across the conveyor simultaneously (while determining the layout of the stations around the loop) versus the traditional method which determines the shortcuts sequentially (after the layout of the stations has

been determined). The proposed methodology also presents an analytical estimate for the work in process at the input stations to the closed looped conveyor.

It is contended that the proposed methodology (using the WIP as a factor in the minimizing function for the facility layout while simultaneously solving for the shortcuts) will yield a facility layout which is less congested than a facility layout generated by the traditional methods (using the total distance traveled as a factor of the minimizing function for the facility layout while sequentially solving for the shortcuts). The proposed methodology is tested on a virtual 300mm Semiconductor Wafer Fabrication Facility with a looped conveyor material handling system with shortcuts. The results show that the facility layouts generated by the proposed methodology have significantly less congestion than facility layouts generated by traditional methods. The validation of the developed analytical estimate of the work in process at the input stations reveals that the proposed methodology works extremely well for systems with Markovian Arrival Processes.

This work is dedicated to Capt. Valerian Lasrado, Merlyn Lasrado, Morgan Lasrado, Felix Pinto, Helen Pinto, Monthie Lasrado, Raymond Lasrado, and the rest of my family.

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LIST OF ACRONYMS / ABBREVIATIONS

Abbreviation	Meaning
ANOVA	Analysis of Variance
CLC	Closed looped conveyor
FLP	facility layout problem
GA	Genetic algorithm
GLM	Generalized Linear Model
LCMHS	Looped conveyor material handling system
LLDP	Looped layout design problem
LLMF	Looped layout manufacturing facility
MF	Manufacturing facility
MFLP	Manufacturing facility layout problem
MHS	Material handling system
PS	Production System
QAP	Quadratic assignment problem
QNA	Queueing network analyzer
SA	Simulated annealing
SCV	Squared coefficient of variation

1 INTRODUCTION

With the ongoing technology battles and price wars in today's competitive economy, every company is looking for an advantage over its peers; an important practical question is, how do companies create this competitive advantage in terms of creating value (Hitt, Ireland, Camp, & Sexton, 2001, 2002; Meyer, 1991)? A sustainable competitive advantage could be provided for by being an efficient business (Peteraf, 1993). As per Tompkins, White, and Bozer (2010), companies in the US spend around 8% of the gross national product annually on new facilities. The authors point out that effective facility planning can reduce operational expenses by 10% to 30% annually. Apple (1977) indicates that a good facility layout design incorporates the material handling decisions at the development stage. Tompkins et al. (2010) indicate that material handling and facility planning cost can attribute around 20% to 50% of a facility's operating expense. Hence, a particular choice of facility Layout can have a significant impact on the ability of a company to maintain lower operational expenses under uncertain economic conditions. Furthermore, a poor Layout can result in high material handling costs, excessive work-in-process (WIP), and low or unbalanced equipment utilization (Heragu, 2006).

In general, the manufacturing facility (MF) consists of a production system (PS) and a material handling system (MHS). The PS consists of numerous operational cells henceforth referred to as a cell or cells. In the literature, a cell in the PS is referred to as a machine, a facility, a station, a collection of stations, a department, a bay, etc. The manufactured units, henceforth referred to as loads or jobs, are transferred from one cell to another by the MHS. As seen in Figure 1.1, there are various types of MF layouts with respect to material handling systems design: single row, multi row, closed loop layout (Kusiak & Heragu, 1987), and open field layout (Loiola, de Abreu, Boaventura-Netto, Hahn, & Querido, 2007).

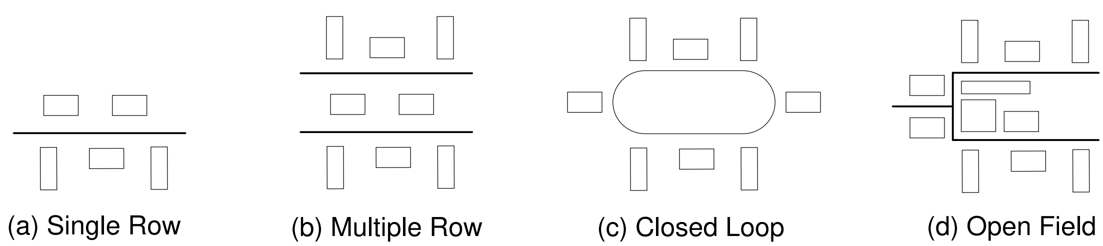

Figure 1.1: Types of facility layouts w. r. t. material handling design

This research will focus on the layout of a MF, i.e., the manufacturing facility layout problem (MFLP) for a closed loop layout. This special case of the MF will henceforth be referred to as the looped layout MF (LLMF). This special case of MFLP will henceforth be referred to as the looped layout design problem (LLDP), using the nomenclature introduced in Nearchou (2006).

The subsequent discussion will first introduce the MFLP, the LLMF and LLDP will be discussed in great detail in § 2.2.1.

The MFLP can be defined as an optimization problem whose solution determines the most efficient physical organization of the cells in a PS with regards to an objective. The most common objectives aim to minimize the material handling cost (MHC), the traveled distance traveled, or the total time in system (Benjaafar, Heragu, & Irani, 2002). Previous MFLP formulations tend to ignore the impact of the facility layout on the operational performance of the MF i.e. the work-in-process (WIP), the throughput, or the cycle time. Benjaafar (2002) shows that traditional MF design criteria can be a poor indicator of the operational performance of the MF. Bozer and Hsieh (2005) too support this argument. Kouvelis, Kurawarwala, and Gutierrez (1992) state, "the use of 'optimality' with respect to a design objective, such as the minimization of the material handling cost, is discriminating." Benjaafar (2002) argues that the operational performance of the MF is contingent on the congestion in the MF. The congestion in the MF is a function of its capacity and variability. Hence, it is imperative that the objective of the MFLP captures the impact of the facility layout on the operational performance of the MF. This can be achieved, for example, by setting the objective of the MFLP to minimize the WIP in the MF

(Benjaafar, 2002; Fu & Kaku, 1997; Kouvelis & Kiran, 1991; Raman, Nagalingam, & Gurd, 2008). However, despite the presence of conveyor systems in high volume manufacturing facilities, there are no methods that generate the Layout by minimizing the WIP in a LLMF with a closed loop conveyor (CLC) as the MHS.

This research proposes a solution methodology that addresses the development of a facility layout for a LLMF with a looped conveyor material handling system (LCMHS) that can have shortcuts across it using a system performance metric, i.e. the work in process (WIP) on the conveyor and at the input stations to the conveyor, as a factor in the minimizing function for the facility layout optimization problem which is solved heuristically using a permutation genetic algorithm. It can be argued that there is no difference in the optimal layout as generated by minimizing the WIP versus the distance or cost, Fu and Kaku (1997) support this claim. Benjaafar (2002) proposes that there is a difference and adds that Fu and Kaku (1997) did not capture this as a result of the simplistic queueing model used to model the MF. Benjaafar (2002) proposes that under certain conditions both approaches will yield the same facility layout, these restricting conditions are:

1. The flow rates between the cells, machines, stations, departments, facilities, or bays are balanced

2. The cells, machines, stations, departments, facilities, or bays are equidistance
3. The demand and process time variability are low

The first condition is practically unrealistic and applies if and only if all the loads visit all the machines the same number of times. Also, modern MFs manufacture a multitude of products and this situation is rarely encountered. As mentioned, this research will focus on MF that have a LCMHS, therefore the second condition in inherently impossible given the MHS is a loop. The third condition is plausible but there are many situations in practice that have high demand variability, high process variability, or both.

Traditionally for the MFLP, the optimal layout of a facility is first determined. After some time of operation, usually if needed, the best set of shortcuts is determined to alleviate congestion in the LLMF as described by Hong, Johnson, Carlo, Nazzal, and Jimenez (2011). It is the contention of the proposed research that the aforementioned two-step process yields a sub-optimal solution. The proposed research aims at determining the best set of shortcuts while simultaneously determining the facility layout, thereby ensuring at worst an equivalent solution to the two-step process.

The computational complexity of the algorithms required to solve the proposed formulation of the MFLP is to be considered. The proposed formulation is a NP-Hard problem as proved by Leung (1992). It has been shown that the computation time required to reach an optimal solution increases exponentially as the number of machines to be arranged increases when using exact solution methods (Foulds, 1983). James, Rego, and Glover (2008) and Loiola, de Abreu, Boaventura-Netto, Hahn, and Querido (2007) supplement this claim with detailed discussions on the computational complexity and the required computation time to reach an optimal solution using exact solution methods. This research proposes the use of genetic algorithms (GA) to solve the formulation as further discussed in § 3.3.1 and §4.

The rest of this chapter is organized as follows: § 1.1 will provide a description of the LLMF; and § 1.2 will present the research statement.

1.1 Description of the LLMF

A brief description of the LLMF is given below. This description entails the assumptions, definitions and characteristics of the LLMF.

It is assumed that the number of machines required and their groupings are predetermined. The machines may be used individually or as a group; in either case, they will be referred to as cells. There will be M cells ($i=1,2,3,..,M$) assigned to N locations ($j=1,2,3,..,N$) where $M \leq N$. If $M < N$ dummy cells ($M+1,M+2,..,N$) are introduced as recommended by Hillier and Connors (1966). There is one entry point (loading cell) and one exit point (shipping cell) to the LLMF. At the entry point ($i=0$) products are delivered/loaded into the plant and at the exit point ($i=N+1$) products are shipped/unloaded out of the plant.

There are K products ($k=1,2,3,..,K$) flowing through the LLMF each characterized by an independently distributed random variable with an average demand (D_k) and a squared coefficient of variation (c_k^2).

The routing for each product through the LLMF is known and is deterministic. Products may visit each cell more than once. The decomposition method as presented in Whitt (1983) is used to determine the internal flows between the cells. The internal flow between cells for each product will be represented by λ_{ij}, where the product travels from cell i ($i=1,2,3,..,N$) to cell j ($j=1,2,3,..,N$) using a LCMHS and $\lambda_{ii}=0$.

The LLMF is a job shop with interconnected bays/cells that each consists of a group of machines or individual machines, an automated material handling system (AMHS) which is a LCMHS with no load recirculation i.e. infinite buffer at unloading station from the conveyor, an input station (where new jobs are introduced to the LLMF) and an output station (where completed jobs are moved away from the LLMF), and shortcuts as shown in Figure 1.2.

The MF has a variable demand, a regular shape with fixed dimensions. The loads can backtrack to cells, i.e. revisit facilities, and bypass cells in the MF. Each cell has a loading / unloading station where loads are loaded to / unloaded from the conveyor.

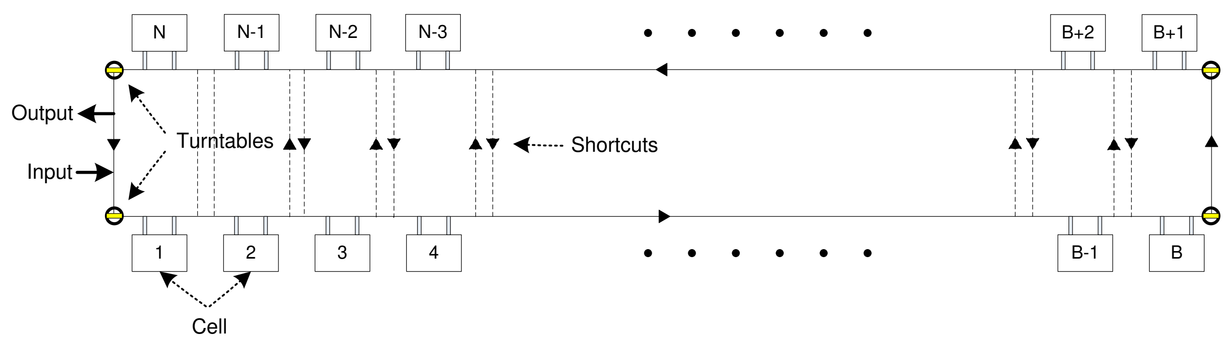

Figure 1.2: Layout of the Facility

The arrival process to cell *i* is characterized by an independently distributed random variable with an average interarrival time ($1/\lambda_i$) and a squared coefficient of variation (c_{ai}^2), while the service process at each cell is characterized by an independently distributed random variable with a mean service time (τ_i) and a squared coefficient of variation (c_{si}^2).

In the LLMF, a shortcut can be placed after each cell i in the direction of flow such that it is before the next cell i+1 and before the corresponding shortcut from the opposite side of the conveyor.

As illustrated by Figure 1.3, two sides of the conveyor are shown. Cell p and cell q are on one side of the conveyor, while cell r and cell s are on the other (opposite) side of the conveyor. The shortcut p (arc 'eh') after cell p is placed in the direction of flow before cell q and before the corresponding shortcut r (arc 'gf') from cell r opposite side of the conveyor.

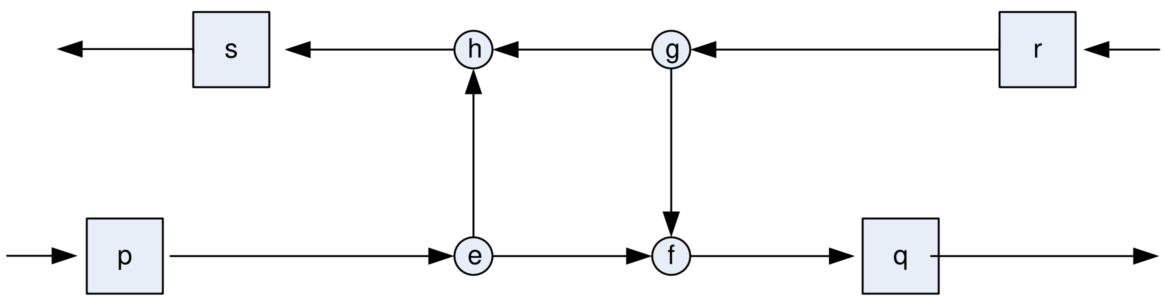

Figure 1.3: Shortcut diagram

If a cell is the last cell on its side of the conveyor in the direction of flow, then a shortcut is always placed after that cell (the short wall of the conveyor that connects the two sides.)

1.2 Research Statement

For a LLMF, the proposed methodology will aim to solve the LLDP for a LCMHS with shortcuts, using a system performance metric, i.e. the work in process (WIP) on the conveyor and at the input stations to the conveyor, as a factor in the minimizing function for the facility layout optimization problem which is solved heuristically using a permutation genetic algorithm.using an operational performance metric, i.e. the work in process on the conveyor and the input stations in a MF, as the minimizing function of the design criteria. Bozer & Hsieh (2005) suggests that for a LLMF, the most appropriate design criterion for the LLDP would be to minimize the total WIP on the conveyor and the input stations for all the cells in the LLMF. Benjaafar (2002) shows that using the total WIP in the system (WIP in the production system, the unloading and unloading stations, and the MHS) as a design criterion for a MF with automated vehicles as the MHS can have a significant impact on the layout of the MF.

As described earlier, most traditional MFLP methods aim at minimizing the total distance traveled, the material handling cost, or the time in the system (based on distance traveled at a specific speed). However, Bozer & Hsieh (2005) suggest that one or more loading stations in the LLMF might become unstable as a result of the traditional layouts creating too much flow over certain segments of the conveyor. Also, one of the outcomes of the proposed research is that the traditional optimal layout, i.e., the layout with the minimum distance may not have the minimum WIP for the LLMF.

Further, as described earlier, the two step process of first determining the optimal Layout and then determining the best set of shortcuts will yield a sub optimal solution. The proposed research addresses this issue by determining the set of shortcuts and the layout simultaneously and iteratively, thereby ensuring at worst an equivalent solution to the two-step process.

The remainder of the document is organized as follows: § 2 will present the literature review with regards to the proposed methodology; § 3 will present the research design; § 4 will present the proposed implementation; and § 5.2.9 will discuss the concluding statements and future work.

2 LITERATURE REVIEW

The amount of research done on the manufacturing facility layout problem (MFLP) is very vast. Due to its broad applicability and solution complexity it has been the subject of active research over the last 50 years. Koopmans and Beckmann (1957) are the first to discuss the FLP. They define the FLP as a quadratic assignment problem (QAP) that determines the layout of facilities so that the material handling cost between the facilities is minimized. Sahni and Gonzalez (1976) prove the computational complexity and the difficulty involved in solving QAP problems by showing the QAP is NP-Complete.

Figure 2.1 on page 14 as presented in (Drira, Pierreval, & Hajri-Gabouj, 2007) illustrates the broad nature of the MFLP. This literature review will focus on the facility layout procedures for a static MF with (refer to

Figure 2.2 on page 15): available data, a variable (stochastic?) demand, a regular shape with fixed dimensions, a looped conveyor based MHS with no load recirculation i.e. infinite buffer at unloading station from the conveyor, with backtracking and bypassing enabled, formulated as a QAP that minimizes material handling cost by minimizing the congestion in the system i.e. the WIP in the manufacturing facility.

The rest of this chapter is organized as follows: § 2.1 will present a list of review papers related to the proposed methodology; § 2.2 will present a review of the MFLP; § 2.3 will present a review of the solution methods for the MLFP; § 2.4 will present a review of conveyor systems and methods of analysis for such systems.

2.1 Review Papers on Research Topic

There have been numerous review and survey papers that have tracked the research on FLP and other research subjects related to the FLP over time pertaining to the current research topic of a LLDP with a LCMHS.

- Wilson (1964) presents a review of various FLP's with regards to fixed designs, material flow networks, and communication networks
- El-Rayah and Hollier (1970) present a review of various FLP while also reviewing optimal and suboptimal algorithms for solving a QAP
- Pierce and Crowston (1971) present a review of algorithms for solving the QAP using tree-search algorithms

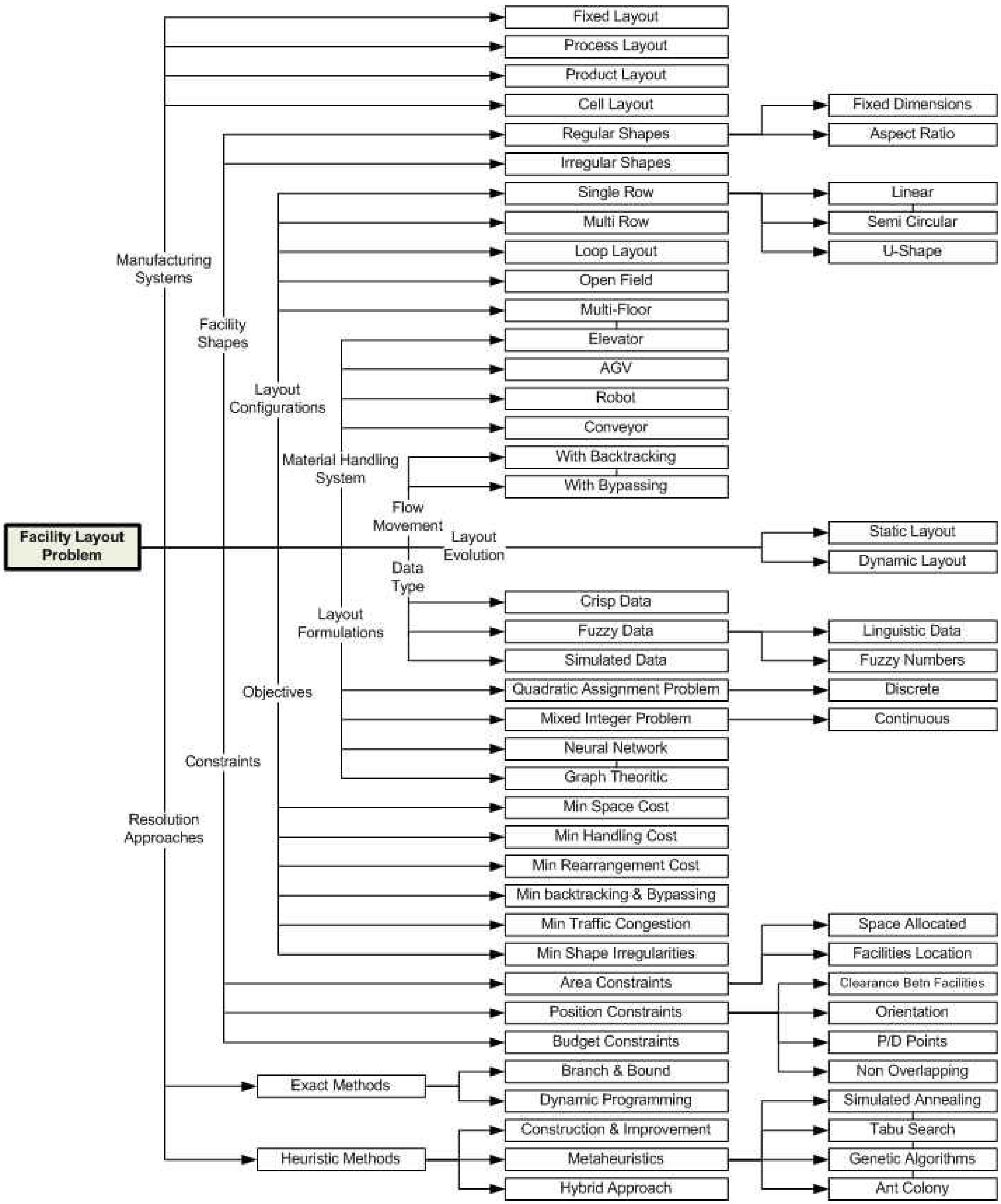

Figure 2.1: Manufacturing Facility Layout Problem Outline

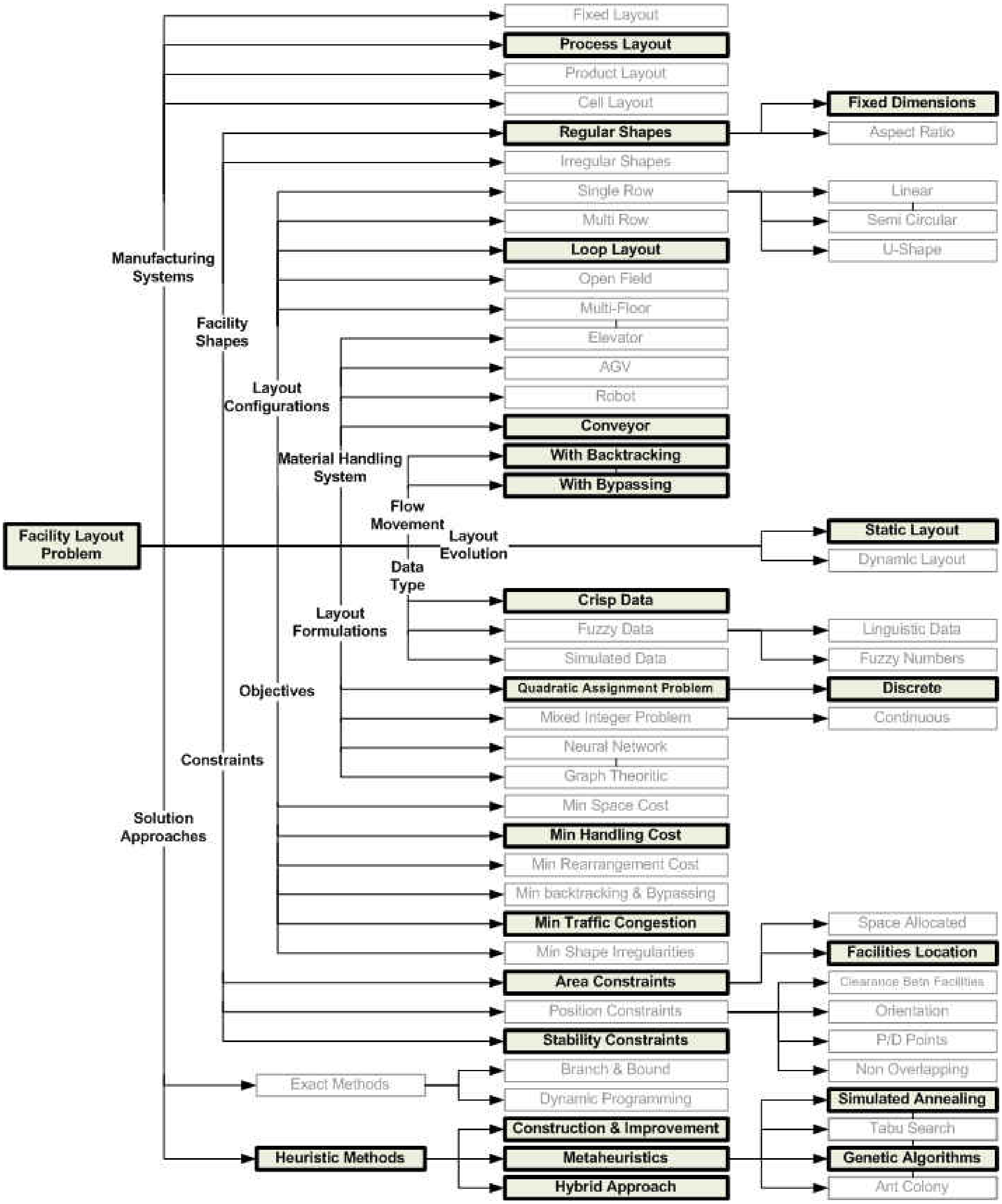

Figure 2.2: Manufacturing Facility Layout Problem Research Focus

- Hanan and Kurtzberg (1972) present a survey of algorithms for solving applications of the QAP to a variety of industries
- Moore (1974) presents a review of the, then, current state of FLP research in Europe and North America based on responses to a survey sent to authors of various FLP algorithms
- Francis and Goldstein (1974) present a list of papers published in between 1960 to 1973 on location theory, however, many of these references allude to the FLP and algorithms used to solve the QAP
- Burkard and Stratmann (1978) present a review that extends the work performed by Pierce and Crowston (1971) by comparing the efficacy of various suboptimal algorithms
- Muth and White (1979) discuss deterministic, probabilistic, descriptive and normative approaches used to model conveyor systems
- Foulds (1983) presents a review of optimal and sub optimal algorithms for the QAP highlighting the application of graph theory to solve the FLP
- Levary and Kalchik (1985) present a review that compares and contrasts several sub optimal algorithms used to solve the QAP

- Buzacott and Yao (1986) present a review that compares and contrasts several analytical models of flexible manufacturing systems by evaluating the strengths and weaknesses of each model
- Finke, Burkard, and Rendl (1987) present a survey of the theory and solution procedures (exact and approximate) for the QAP with special interest devotes to integer programming equivalents to the QAP
- Hassan and Hogg (1987) present a review and evaluation of algorithms that apply graph theory to solve the FLP
- Kusiak and Heragu (1987) present a review that evaluates the, then, current state of optimal and suboptimal algorithms to solve the FLP
- Bitran and Dasu (1992) present a review of manufacturing systems modeled as open queueing networks
- Pardalos, Rendl, and Wolkowicz (1994) present a survey of the, then, current state of QAP research covering QAP formulations, solution methods and applications
- Meller and Gau (1996) present a survey that compares and contrasts the, then, current FLP software to the FLP research

- Mavridou and Pardalos (1997) present a survey of simulated annealing algorithms and genetic algorithms used for generating approximate solutions for the FLP
- Balakrishnan and Cheng (1998) present a review of the algorithms to solve the FLP based on multiple periods planning horizons (Dynamic FLP[1]) as opposed to static unchanging layouts
- Govil and Fu (1999) present a survey of queueing network models for the analysis of various manufacturing systems by identifying the main factors affecting the models as well as variations of the models
- Pierreval et al. (2003) present a review of manufacturing facility layout where evolutionary principles have been applied to optimize the MFLP
- Haupt and Haupt (2004) present a detailed review and analysis of GAs and the practical application of GAs with examples of executable Matlab and Fortran code.

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[1] The current research will focus on static facility layouts although future work will extend the static facility layout model to a dynamic facility layout model

- Asef-Vaziri and Laporte (2005) present a review of loop based facility planning methodologies for MF with trip based MHS i.e. automated guided vehicles (AGV)
- Agrawal and Heragu (2006) present a review of automated material handling systems (AMHS) used in Semiconductor Fabs
- Singh and Sharma (2006) present an exhaustive survey of various algorithms as well as computerized facility layout software developed since 1980 for the FLP
- Drira, Pierreval, and Hajri-Gabouj (2007) present a review of algorithms for the FLP along with a generalized framework for the analysis of literature with regards to FLP as shown in Figure 2.1 on page 14
- Loiola et al. (2007) present a survey of QAP and associated procedures by discussing the most influential QAP formulations and QAP solutions procedures
- Nazzal and El-Nashar (2007) present a survey of models of conveyor systems in semiconductor fabs and an overview of the corresponding simulation based models.
- Shanthikumar, Ding, & Zhang (2007) present a survey of the application of queueing theory literature to semiconductor manufacturing systems

2.2 Manufacturing Facility Layout Problem

This section first presents a review of the general MFLP formulations where M facilities / cells are assigned to N locations with regards to a certain objective. The most common objectives aim to minimize the material handling cost (MHC), the distance traveled, or the total time in system (Benjaafar, Heragu, & Irani, 2002). The proposed research will formulate the LLDP as a QAP to generate an optimal layout for a LLMF. Second, a review of the LLDP is presented in § 2.2.1 on page 22. Third, a review of MFLP formulations with that minimize the WIP in the MF is presented in § 2.2.2 on page 28.

The MFLP is formulated as a QAP by Koopmans and Beckmann (1957). Sahni and Gonzalez (1976) show that the QAP is NP-Complete. Given that there are M cells and N locations, if $M < N$ dummy cells ($M+1, M+2, .., N$) are introduced as stated in Hillier and Connors (1966). The following notation is used where x_{ij} is the decision variable:

λ_{ik} – flow of loads from cell i to cell k

c_{ji} – cost of transporting load from location j to location l

x_{ij} – 1 if cell i is at location j; 0 otherwise

$$\text{Min} \quad \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} \lambda_{ik} c_{jl} x_{ij} x_{kl} \qquad (1)$$

$$\text{s.t.} \quad \sum_{i=1}^{N} x_{ij} = 1 \qquad \forall j, 1 \le j \le N \tag{2}$$

$$\sum_{j=1}^{N} x_{ij} = 1 \qquad \forall i, 1 \le i \le N \tag{3}$$

$$x_{ij} \in \{0,1\} \qquad 1 \le i, j \le N \tag{4}$$

The formulation as presented in (1)-(4) minimizes the transportation cost of a MF. Given that d_{ji} is the distance between location j and location l; (1) can be restated as follows to generate a layout that minimizes the total distance traveled by the loads in a MF.

$$\text{Min} \quad \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} \lambda_{ik} d_{jl} x_{ij} x_{kl} \tag{5}$$

s.t. (2)-(4)

As indicated by Loiola et al. (2007), there are various formulations of the FLP; all of these formulations can be traced back to the QAP. Examples of such formulations include: quadratic set covering problem (QSP) formulation (Bazaraa, 1975), linear integer programming formulation (Lawler, 1963), mixed integer programming formulation (Bazaraa & Sherali, 1980; Kaufman & Broeckx, 1978), graph theoretic formulation (Foulds & Robinson, 1976), formulations by permutations (Hillier & Connors, 1966), and trace formulations (Edwards, 1980).

The proposed research will focus on the formulation by permutations as it is the most commonly used formulation and extends itself well to formulations with very complicated objective functions. According to Hillier and Connors (1966) and Loiola et al. (2007) if S_N is the set of all permutations of N variables, $\pi \in S_N$, and $C_{\pi(i)\pi(j)}$ is the cost of transporting load from location $\pi(i)$ to location $\pi(j)$. Then, given that each permutation (π) represents a unique layout of the MF, i.e. a unique assignment M cells to N locations, the MFLP that minimizes the transportation costs in the MF reduces to:

$$\min_{\pi \in S_N} \quad \sum_{i=1}^{N} \sum_{j=1}^{N} \lambda_{ij} c_{\pi(i)\pi(j)} \tag{6}$$

Loiola et al. (2007) state that the above formulation is equivalent to (1)-(4), as (2) and (3) define a matrix $\boldsymbol{X} = [x_{ij}]$ for each π related to S_N as in (6), where for all $1 \leq i, j \leq N$,

$$x_{ij} = \begin{cases} 1, & \text{if } \pi(i) = j; \\ 0, & \text{if } \pi(i) \neq j. \end{cases} \tag{7}$$

2.2.1 Looped Layout Design Problem (LLDP)

The LLDP is a special case of the MFLP applied to LLMF. LLMF's are attractive due to their low setup costs as the LLMF requires minimal material handling resources to link the various cells to each other (Afentakis, 1989). By design, in a LLMF all the cells are easily accessible (Afentakis, 1989). There are two types of layout patterns: the closed loop layout that has a predetermined pattern and the open field type layout that has no predetermined pattern. Chae and Peters (2006) indicate that the latter is more difficult to solve and may result in less desirable solutions as a result of the lack of modularity and/or structure in the pre-scribed layout of the LLMF.

As in the case of the MFLP, the LLDP aims to determine the most effective arrangement of *M* cells to *N* locations (around a loop) with regards to a certain objective. The most common objective for the LLDP is to minimize the material handling cost (Asef-Vaziri & Laporte, 2005). Most of the current research of the LLDP is geared towards LLMF's with AGV's as the MHS (Asef-Vaziri & Laporte, 2005; Nearchou, 2006), Bozer and Hsieh (2005) present a solution to the LLDP for a LLMF with a closed loop conveyor as the MHS. Kouvelis and Kim (1992) and Leung (1992) show the LLDP is NP-Complete. As in the case of MFLP, meta-heuristic solution approaches are most effective to solve LLDP with greater than 20 cells (Asef-Vaziri & Laporte, 2005).

Afentakis (1989) is the first to propose an algorithm to explicitly design the layout of LLMF. Afentakis (1989) proposes to minimize the traffic congestion, which can be defined as the number of times a load traverses the loop before it departs from the system. Afentakis (1989) proposes a heuristic based on a graph theoretic approach to minimize the traffic congestion of all the loads (also referred to as MIN-SUM). The heuristic constructs a layout from the dual of a linear programming (LP) relaxation of the problem. Afentakis (1989) was able to solve a LLDP with up to 12 cells.

Leung (1992) builds on Afentakis (1989) by proposing a heuristic based on a graph theoretic approach to minimize the maximum traffic congestion of all the loads (also referred to as MIN-MAX). Kaku and Rachamadugu (1992) model the LLDP as a QAP and find optimal and near optimal solutions for smaller problems.

Millen, Solomon, and Afentakis (1992) analyze the impact of the number of loading and unloading stations on the material handling requirements for a LLDP using simulation. They point out that having a single loading and unloading station for the LLDP increases the material handling requirements by as much as 200% versus having a loading and unloading station at each cell.

Kouvelis and Kim (1992) propose an algorithm to solve the LLDP. By using the formulation as described by (6), they develop dominance relationships to easily identify local optimal solutions thereby reducing the solution space. They develop and apply a branch-and-bound procedure and heuristic methods successfully to a LLDP with 12 cells.

Kiran and Karabati (1993) present a branch-and-bound procedure and heuristic methods for a LLDP. As in Kouvelis and Kim (1992), Kiran and Karabati (1993) too present dominance rules based on a special distance metric to identify local solutions. They present a special case of the LLDP / QAP that is solvable in polynomial time. When all the cells in a LLMF interact with only one cell, the LLDP can be solve in $O(n^2 \log n)$ time.

Das (1993) presents a four step heuristic procedure for solving the LLDP that combines variable partitioning and integer programming to minimize the total projected travel time between cells. Each cell is represented by its special coordinate, its orientation with respect to the layout (horizontal or vertical), and the location of its loading or unloading station. The heuristic becomes computationally inefficient for problems with greater than 12 cells.

Banerjee and Zhou (1995) present a formulation of the LLDP as a specialization of the flow network based MFLP proposed by Montreuil (1990). The method as proposed by Montreuil (1990) is more complicated as the physical considerations of the cells are taken into account (Afentakis (1989) and related methods ignore the dimensional characteristics of a cell and its relationship to the locations it is assigned to.) The cells are assumed to be rectangular and the dimensions are the decision variables.

Cheng, Gent, and Tosawa (1996) and Cheng and Gen (1998) extend Afentakis (1989) by applying a genetic algorithm with a modified mutation process to solve the LLDP by investigating its performance on both MIN-SUM and MIN-MAX congestion measures. A nearest neighbor local search is used to determine the best genes to mutate.

Tansel and Bilen (1998) present a solution to the LLDP by proposing a heuristic that applies positional moves and local improvement algorithms based on k-way interchanges or swaps between cells in a particular layout so as to determine the best layout for the LLMF.

Bennell, Potts, and Whitehead (2002) present a local search and a randomized insertion algorithm for the MIN-MAX LLDP. The proposed method is an extension of Leung (1992) that overcomes the implementation difficulties, computational requirements, and generates better solutions with respect to Leung (1992).

Bozer and Hsieh (2005) analyze the performance of a LCMHS with fixed windows. A stability factor (SF) for the LCMHS is derived by determining the maximum utilization of the loading stations along the LCMHS. The utilization at each loading station is characterized by the speed of the LCMHS, the arrival rate to the loading stations, and the flow rate on the conveyor segment leading up to each loading station. The system is the stable if *SF* < 1. A methodology is presented to estimate the WIP on the LCMHS. A proof is provided to show that minimizing the WIP on the LCMHS is equivalent to minimizing the distance traveled by the loads. Using this result, a methodology is presented to generate the optimal layout of stations around the LCMHS by minimizing only the WIP on the LCMHS with maximum value the SF as a user defined constraint. Their research does not address the WIP at the loading station of the LCMHS.

Yang, Peters, and Tu (2005) propose a two-step heuristic procedure to solve the LLDP. The first step of the solution methodology determines the Layout as proposed by Montreuil (1990) to minimize the material handling costs by using a combined space filling curve and simulated annealing algorithm. Then, the output from the first step is used to solve the LLDP using a mixed integer programming formulation.

Chae and Peters (2006) propose a simulated annealing heuristic for the LLDP that build on an earlier method proposed by Das (1993). They apply an open field type layout method to generate a closed loop layout, thereby generating much better solutions in terms of minimizing material movement while maintaining layout modularity and structure.

Öncan and AltInel (2008) present two exact solution approaches for LLDP: a dynamic programming algorithm and a branch and bound scheme. They also present new upper and lower bound procedures for the QAP using the branch and bound scheme.

Ozcelik and Islier (2011) present a methodology for optimizing the number of loading and unloading stations while determining the layout the LLDP. However, the proposed methodology uses the traditional decision criterion for the objective function, i.e. aims to generate a layout that minimizes the total distance travelled.

2.2.2 Formulations with Minimum WIP design objective

There is extensive literature for the MFLP with the design objective of minimizing the material handling cost, the travel time in system, or the total distance traveled by the loads in the system. There are numerous literature review and survey papers as presented in § 2.1 on page 16 on this subject matter. However, these traditional criteria for design can be poor predictors of the operational performance of a MF. The papers presented in this section are the few approaches that propose to solve the MFLP using the operational performance of a MF as the design criteria, this approach will be utilized by the proposed research.

Solberg and Nof (1980) present a mathematical model based on queueing network theory for the analysis of various Layout configurations for a MF. The method presented is not a MFLP but rather an attempt to explicitly develop an alternative design criterion for the MFLP.

Kouvelis and Kiran (1991a, 1991b) and Kouvelis et al. (1992) present the MFLP formulated as a QAP with the objective of minimizing the material handling cost and the WIP holding cost for a MF with AGV's as the MHS over single and multiple periods.

Fu and Kaku (1997a, 1997b) present a MFLP with the objective on minimizing the average WIP for the MF. The objective function is similar to that used in Kouvelis and Kiran (1991a, 1991b), i.e., minimizing the material handling cost and the WIP holding cost for a MF with AGV's as the MHS over a single period. They made numerous simplifying assumptions to model the queueing network as a Jackson network so as to obtain a closed form expression of the average WIP. They show that there is no difference between the traditional facility design objective and the tested objective that take the operational performance as the design criteria.

Benjaafar (2002) extends Fu and Kaku (1997a, 1997b) by relaxing several assumptions and using the queueing network analyzer as presented by Whitt (1983a). Benjaafar (2002) shows that when some of the assumptions made by Fu and Kaku (1997a, 1997b) are relaxed, the claim of equivalent outcomes between the two formulations is not always valid. Benjaafar (2002) shows that under general conditions the layouts generated by the two formulations can be very different. The key difference between Benjaafar (2002) and Fu and Kaku (1997a, 1997b) is that as a result of using the QNA, Benjaafar (2002) is able to capture the interaction between the various systems in the MF that were absent in Fu and Kaku (1997a, 1997b). Raman et al. (2008) extend Benjaafar (2002) for MF's with unequal area cells.

Johnson, Carlo, Jimenez, Nazzal, and Lasrado (2009) present a greedy heuristic for determining the best set of shortcuts for a LLMF with a LCMHS.

Hong et al. (2011) extend Johnson et al. (2009) and present a methodology for determining the location of shortcuts for a LLMF with a LCMHS using WIP as the decision criterion.

2.3 Solution Methods

The various algorithms used to revolve MFLP formulated as a QAP can be categorized into: exact algorithms, heuristic algorithms, and meta-heuristic algorithms. As a result of the choice of design objective, i.e. generate a layout that minimizes the average WIP in the MF/LLMF, the exact and heuristic solution methods cannot be used to solve the proposed LLDP as further discussed in § 3.3.1 on page 70.

Two recent review papers (Drira et al., 2007; Loiola et al., 2007) indicate that meta-heuristic approaches are the most popular solution methods. These methods are able to cope with large problem sizes and are able to effectively solve an optimal or near optimal solution. The proposed research will utilize the meta-heuristic approach to solve the LLDP formulated as a QAP, more specifically, genetic algorithms (GA) to solve the LLDP. However, for sake of completeness, a brief overview of other methods and algorithms used to solve the MFLP will be presented in the subsequent sections.

Exact solution algorithms are limited as a result of computational inefficiencies and computer memory issues. As discussed earlier, Foulds (1983) show that when using exact solution methods the computation time required to reach an optimal solution increases exponentially as the number of cells to be arranged increases. This outcome is reiterated by James, Rego, and Glover (2008) and Loiola, de Abreu, Boaventura-Netto, Hahn, and Querido (2007) who present detailed discussions on the computation complexity and the required computation time to reach an optimal solution using exact solution methods. This shortcoming of the exact algorithms has led to the development of many heuristic approaches to solve the MFLP. With the development of sophisticated generally applicable meta-heuristic algorithms, the older problem specific heuristic algorithms have lost favor with practitioners.

2.3.1 Exact Algorithms

There are two types of exact solution algorithms used to determine the global optimum for the MFLP formulated as a QAP: branch and bound algorithms and cutting plane algorithms (Kusiak & Heragu, 1987). In general, exact solution methods implement controlled enumeration as a means to obtain the optimal solution while not enumerating through all the possible solutions (including infeasible solutions) i.e. total enumeration. The examination of the lower bounds for the QAP is crucial to the development of efficient and expeditious controlled enumeration based exact solution methods. A good lower bound procedure will yield values close to the optimal value for the QAP (Loiola et al., 2007).

The branch and bound algorithm is the most commonly implemented and most researched exact solution algorithm. This algorithm is first presented independently by both Gilmore (1962) and Lawler (1963), the algorithms differ in the computation of the lower bound used to eliminate undesired solutions. The lower bound procedures as presented by Gilmore (1962) and Lawler

(1963) are the most popular procedures due to their simplicity and efficiency in terms of computational requirements. These lower bound procedures are limited in that for larger problems they provide weak lower bounds.

Bazaraa and Sherali (1980) present the cutting plane algorithm. This algorithm is computationally inefficient and requires a large amount of computer memory and works well only for small problem sizes.

2.3.2 Heuristics Algorithms

Problem specific heuristic algorithms have lost favor to more generally applicable meta-heuristic algorithms. The following discussion provides a brief overview of heuristic algorithms, more detailed description of the heuristic algorithms is provided by Kusiak and Heragu (1987). There are two broad categories of heuristic algorithms in the literature: Construction algorithms, and improvement algorithms.

In construction algorithms each cell is assigned to a location individually until the layout is obtained, i.e. the solution is constructed ab initio. Improvement algorithms begin with a randomly generated initial solution and try to improve it by systematic assigning cells to locations. The assignment yielding the best solution is retained and the process is repeated until no further improvement is possible or a stopping criterion is met.

2.3.3 Meta-Heuristic Algorithms

Meta-heuristic algorithms have gained much traction since 1980 and have been applied to a wide variety of optimization problems. In general, meta-heuristic algorithms build on the theory and application of natural process to the resolution of the QAP by iterating until a stopping criterion is satisfied. A very important step for all these algorithms is parameter selection at the initialization of the algorithm. By effectively varying the parameters, convergence to poor local minima can be avoided. This feature makes meta-heuristic algorithms very attractive as they usually generate optimal or near optimal solutions for very complicated problems that cannot be solved by exact and heuristic algorithms.

This review will focus on the application of meta-heuristc algorithms to the MFLP/LLDP formulated as a QAP. Drira et al. (2007) and Singh and Sharma (2006) indicate that genetic algorithms are the most popular meta-heuristic algorithms used to solve the MFLP formulated as a QAP. The proposed research will implement a genetic algorithm based solution procedure to solve the LLDP. However, for completeness, other meta-heuristic algorithms such as simulated annealing and Particle Swarm Optimization will be briefly discussed.

2.3.3.1 Genetic Algorithms

Genetic algorithm methodology (GA) is introduced by Holland (1975) and popularized by Goldberg (1989). Since its introduction, GA's have greatly influenced many solution procedures for complex optimization problems.

GA is a selection and optimization technique that solves an optimization problem by adopting the principles of natural selection and genetics to traverse through the search space to find the global optimal solution. There are two broad categories of GAs: discrete GAs and continuous GAs. The proposed research will implement a discrete GA; hence this review will focus on presenting a broad overview of discrete GAs and their applications to the QAP. There have been numerous applications of the GA to solve the FLP (Balakrishnan & Cheng, 2000; Balakrishnan, Cheng, Conway, & Lau, 2003; Benjaafar, 2002; Chan & Tansri, 1994; Cheng & Gen, 1998; Cheng et al., 1996; Cheng, Gent, & Tozawa, 1995; El-Baz, 2004; Ficko, Brezocnik, & Balic, 2004; Islier, 1998; Kochhar, Foster, & S Heragu, 1998; Lee, Han, & Roh, 2003; Mak, Wong, & Chan, 1998; Rajasekharan, Peters, & Yang, 1998; Raman et al., 2008; Suresh, Vinod, & Sahu, 1995; Tam, 1992; Tate & Smith, 1995; Tavakkoli-Moghaddain & Shayan, 1998;

M. Wang, Hu, & Ku, 2005; Wu, Chu, Wang, & Yan, 2007). In general, these methods follow the framework as presented in Figure 2.3; hence, to avoid redundancy, a general detailed overview of GA is presented.

The material discussed henceforth is from Haupt and Haupt (2004), unless stated otherwise. Figure 2.3 illustrates the general flowchart for a GA. The cost function, or as it is sometimes referred to as the fitness function, is the function over which the GA attempts to solve the optimization problem. The cost function could be a mathematical function, an experiment, etc. There are several user defined parameters (in between 0 and 1) in the GA: the selection rate, the crossover rate, and the mutation rate. These parameters are introduced and described in the following description of the GA.

The proposed research uses the average WIP on the LLMF as the cost function. The GA begins by defining a chromosome as an array of the decision variable values to be optimized. For the FLP, the chromosome is represented by a string of values that indicate if a particular cell is at a particular location as described by the decision variable. Each chromosome is a unique Layout configuration of the MF i.e. candidate solution to the FLP.

The GA starts with an initial set of randomly generated chromosomes (initial solutions). Next, the cost for each chromosome is evaluated. At this stage, the idea of 'survival of the fittest' is applied, in that; the best solutions (chromosomes) are selected to be mated according to a selection rate.

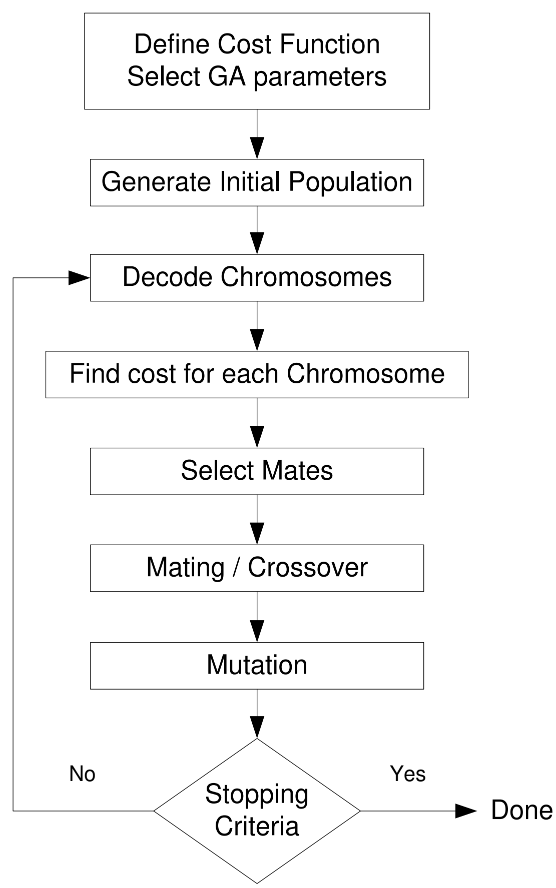

Figure 2.3: Flowchart of a GA

From the set of selected chromosomes a predefined number of chromosomes (parents) are selected to be mated according to:

a) Pairing the best with the worst

b) Random pairing

c) Weighted random pairing: where the best chromosomes are assigned higher mating probabilities which give them the best likelihood of mating

d) Tournament selection: It mimics mating competition in nature; a small subset of two to three chromosomes is randomly selected. From this subset, the best chromosome is selected. The process is repeated until the required number of parents is reached.

Weighted random pairing and tournament selection are the most commonly used selection schemes used to determine the set of parents to be mated. The most common form of mating involves a pair of parents producing a pair of offspring. For each parent a crossover point is determined by multiplying the length of the chromosome (the number of characters / bits in the string of decision variables) by the crossover rate. In some mating / crossover schemes multiple crossover points are determined. Therefore, for each parent there could be two of more chromosomes ready for mating. The offspring generated have one or more parts of each parent's chromosome to form a new chromosome i.e. a new unique solution. This is one way in which the GA traverses through the problem space.

This operation is better illustrated with an example. Let P1 and P2 be the two parents with offspring O1 and O2. The chromosomes for each parent are P1=[111111] and P2=[000000]. As it can be seen the length of the chromosome is 6 (as each chromosome characterized by 6 bits). In this case, the parent chromosome is split into two parts as determined by the crossover point that is derived by applying the crossover rate over the number of bits in the chromosome. If the crossover rate is 0.4, the crossover point is at 0.4*6 = 2.4 bits which is rounded down to 2 bits. The chromosomes for parents can be rewritten as P1=[11 1111] and P2=[00 0000]. The offspring are given as follows O1=[110000] and O2=[001111].

Mutations alter a certain portion of the chromosome. Mutation is another operation by which the GA traverses through the problem space. As a result of mutation, the new population has traits not inherent to the original population. Hence, by introducing the mutation operation the GA is prevented from converging too quickly to a local solution prior to sampling the problem space. At this point an elitist methodology is recommended. The previous best solution is retained in memory, if none of the mutations improve upon this solution it is re-introduced into the population set. This method of keeping track of the best solution, i.e. the elitist methodology, inadvertently enables the GA to converge to the global optimal solution after a certain number of iterations. In the illustrated example, a mutation to the offspring 02 could be O2=[***1***01***0***11] as indicated by the numbers that are bold and italic in O2. The mutation is brought about by changing the 0 to ***1***, and a 1 to ***0***.

The next step is to check for the stopping criteria. If the stopping criterion is not met, the processes are repeated as shown in Figure 2.3 on page 37. In general, there are two stopping criteria most commonly used in the literature:

a) No statistically significant improvement in X number of iterations

b) A certain number of iterations have been completed

One may question whether the solution generated by the GA is the global optimal solution, or if there exists a proof of convergence for the GA. Holland (1975) presents a loose proof of convergence for the GA called the schema theorem which a logical argument that states: by design the GA favors the best chromosomes and as a result of the selection process the GA will eventually converge to the global optimal solution. Greenhalgh and Marshall (2000) present $t(\delta)$ as a lower bound for the number of iterations (a large number) required to assure the GA converges to the global optimal solution with an associated probability δ. Rudolph (2002) supports this claim and further adds that, "convergence to the global optimum is not an inherent property of the GA but rather is a consequence of the algorithmic trick of keeping track of the best solution (the elitist methodology) found over time.” Rudolph (2002) proves that if the mutation operation is unchanged the GA will have a chance of converging to the global optimal if and only if the selection operation is changed i.e. varied as the iterations progress. Rudolph (2002) also proves that the GA could possibly converge to the global optimal solution by the introduction of time variant, i.e. after a certain number of iterations, mutation, crossover, and selection rates. As with the other meta-heuristic approaches proper initial parameter selection can ensure the quality of the solution. De Jong (1975) presents the following observations on choice of initial parameters:

a) Small population sizes improve initial performance
b) Large population sizes improve long-term performance
c) High mutation rates are good for offline performance, where offline performance is the running average of the best cost solution found in each generation
d) Low mutation rates are good for online performance, where online performance is the running average of all cost solutions up to the current generation
e) Crossover rate should be around 0.60

2.3.3.2 Particle Swarm Optimization

Eberhart and Kennedy (1995) and Kennedy and Eberhart (1995) introduce particle swarm optimization (PSO). This algorithm is inspired by the flocking behavior of flocking animals. The PSO is similar to the GA; it begins with a randomly selected population of possible solutions referred to as particles. However, there are no evolutionary operations such crossover and mutation as in the case of the GA.

The PSO algorithm adjusts the trajectories of a population of "particles" through a problem space on the basis of information about each particle's previous best performance and the best previous performance of its neighbors (Kennedy & Eberhart, 1995). The performance of the PSO algorithm is impacted by choice of the initial parameters as further discussed by Shi and Eberhart (1998). Kennedy and Eberhart (1997) present a discrete version of PSO where particles take on zero or one values.

2.3.3.3 Simulated Annealing

Simulated annealing is introduced by Kirkpatrick (1984). Burkard and Rendl (1984) present an application of simulated annealing for the QAP. This algorithm simulates the annealing of solids. The algorithm associates the objective function values of feasible solutions of the optimization problem to energy states of a physical system. In nature, a stable system is the system with global minimum energy state. The simulated annealing algorithm attempts to simulate the process of attaining the global minimum of the specified problem. As in the physical world, a system moves to more stable if the energy of the current state is lower than the previous state, likewise in simulated annealing a new preferred solution is accepted if it improves on an existing solution. More specifically, a solution that is a neighboring solution to the current one is generated with a probability. This probability depends on the difference between the functions of the two solutions and a temperature; a gradually decreased parameter. This process is repeated iteratively until no further improvement is possible or a stopping criterion is reached. Several initial parameters must be specified as recommended by Laarhoven and Aarts (1987), the choice of which determines the quality of the solution.

2.3.3.4 Tabu Search Algorithm

Tabu search (TS) algorithm is introduced by Glover (1989, 1990). It is an evolutionary algorithm that maintains and updates a list (tabu list) of best solutions, each receiving a priority value, found via the search process. A methodology is presented to accept or reject new solutions in the neighborhood of older solutions based on the tabu list information and the priorities. In many ways, the TS algorithm is a randomized local optimization algorithm that iteratively traverses through the search space to find the global optimal solution by maintaining a tabu list of previously evaluated solutions.

2.4 Conveyor Analysis

Conveyor Systems have been studied over the last half century as a MHS in MF’s with the combined purpose of transferring and storing manufacturing units (loads). This research will focus on MF’s with LCMHS as the MHS i.e. a LCMHS. The LCMHS operates at a constant conveyor speed with fixed windows and no load recirculation. The loading and unloading stations to and from the LCMHS are assumed to have infinite capacity. Research papers that cover the load recirculation problem (Bastani, 1988; Bastani & Elsayed, 1986; Hsieh & Bozer, 2005; Pourbabai & Sonderman, 1985; Schmidt & Jackman, 2000; Sonderman, 1982) are not currently considered, however, future extensions of the proposed methodology will be explored to include the load recirculation problem.

Kwo (1958) is the first to analyze LCMHSs. He develops a deterministic model of loads traveling between two stations on a LCMHS. He proposes three intuitive yet fundamental principles to ensure the LCMHS operates satisfactorily: (1) The speed of the LCMHS must operate within its permissible range (speed rule); (2) The LCMHS must have enough capacity to meet the manufacturing systems demands (capacity must have enough capacity to meet the manufacturing systems demands (capacity rule); (3) The LCMHS must be loaded and unloaded uniformly i.e. the number of loads loaded on the LCMHS must equal the number of loads unloaded from the LCMHS (uniformity principle). However, this paper does not present work on estimating performance measures for LCMHSs.

Kwo's work is analytically modeled by Muth (1972) for LCMHSs with continuous loads and by Muth (1974) for LCMHSs with discrete spaced loads. (Muth, 1974) presents an analytical model, for a system with deterministic flow rates, whose solution yields the stable operating conditions of LCMHSs (determines the minimum number of bins required) with one loading and one unloading station.

In Muth (1975), he extends his previous work for the case of multiple loading and unloading stations by solving a difference equation that reflects the dynamics of the multi-station system with deterministic flow rates.

Muth (1977) presents an analytical solution for the probability distribution of the material flow leaving the unloading station for a LCMHS with one loading and one unloading station is considered. The results show that the LCMHS reduces the random fluctuations in the input flow. This smoothing effect is quantified by a variance reduction factor which is the ratio of the variances of output flow and input flow. However, this study is limited to systems with one loading and one unloading station.

Mayer (1960) presents the first probabilistic model of a LCMHS system with one loading and one unloading station that describe the functional aspect of transferring loads to and from a loading station while enabling the windows to hold multiple loads.

Morris (1962) extends Mayer's work to include multiple grouped loading stations followed by multiple grouped unloading stations. The separate grouping of loading and unloading stations is not very conducive to most real world settings.

Coffman Jr, Gelenbe, and Gilbert (1986) develop an analytical model of a LCMHS system with one loading and one unloading station with the aim of determining the optimal distance, in terms of number of windows, between the loading and unloading station on the conveyor. The solution is mathematically intense and can often lead to very complicated unsolvable expressions for the moment generating function for the number of windows. However, their work highlights the importance of the location of the loading and unloading stations that is often overlooked in both research and practice.

Pourbabai (1986) analyzes the effect of external variability of the flow rates on the performance of a LCMHS system with one loading, one unloading station, and recirculation of loads. The production system is modeled as G/G/1/0 queuing system with retrials, stationary counting arrival process, generally distributed service times, and no waiting room. The flow of load within the manufacturing facility is recursively estimated using a renewal process. One of the key outcomes of this research is that a streamlined loading process aids in reducing the congestion on the MHS. Most of the loading stations at LCMHS's in modern manufacturing facilities have robots that have a deterministic service time which is less that the cycle time (the time it takes one window to pass) of the conveyor (Nazzal & El-Nashar, 2007).

Atmaca (1994) analyzes the performance of a manufacturing system with unreliable machines and a LCMHS with fixed windows. An approximate method is presented that calculates the total time in system for the loads, and the WIP for the manufacturing system with a LCMHS with multiple loading and unloading stations. The system is decomposed into individual sections which are then analyzed in isolation. The loading stations and unloading stations to the conveyor are equipped with a queue hence there is no load recirculation or loads lost to the LCMHS system. It is the first work that approximates number in queue (WIP) and time in queue at the loading stations by modeling the loading stations as a G/G/1 queue.

Bozer and Hsieh (2004) propose an approximate method to estimate the waiting times at the loading stations in a LCMHS. The setup of loading and unloading stations is similar to that proposed by Atmaca (1994). Atmaca (1994) assumes adjacent windows on the conveyor are independent, however, the authors propose that a better estimate of the expected wait times at the loading stations can be achieved by considering correlated adjacent windows.

Nazzal, Johnson, Carlo, and Jimenez (2008) presented a model that approximates the WIP on a LCMHS with multiple loading station and turntables. The LCMHS can be thought of as being 4 straight line conveyors in a rectangle each connected to the other by a turntable. This model is catered to semiconductor wafer fabs (Nazzal & El-Nashar, 2007). The LCMHS is divided into segments, the WIP on each segment is calculated as prescribed by Bozer and Hsieh (2005) while the WIP at the turntables estimated by modeling the turntables as M/D/1 queue (Buzacott & Shanthikumar, 1993).

Nazzal et al. (2010) extend Nazzal et al. (2008) by approximating the WIP on a LCMHS with shortcuts. The LCMHS is decomposed into sets of cells. Each set of cells is formed using adjacent and opposite cells. The WIP for each cell is then estimated using standard queueing procedures. The total WIP is

This chapter has presented a review of the literature dealing with the proposed research. The next chapter will present the research design.

3 RESEARCH DESIGN

The proposed methodology will aim to solve the LLDP for a LLMF with a LCMHS with shortcuts, using an operational performance metric, i.e. the work in process on the conveyor and the input stations in a manufacturing facility, as the minimizing function of the design criteria.

3.1 Conveyor Analysis

This section presents a queueing-based analytical model to estimate the expected work-in-process (WIP) and the associated delays of the jobs traveling on the LCMHS as presented in Nazzal et al. (2008) in two phases as described in § 3.1.1 and § 3.1.2. The introduction of shortcuts across the LCMHS introduces some delays and congestion into the LLMF as presented in Nazzal et al. (2010) as described in § 3.1.3. The value of the proposed model is that it would allow designers to quickly and accurately evaluate the expected performance of LCMHS. One may skip over § 3.1.2, if turntables are not considered in the design.

Figure 3.1 illustrates the LLMF. The system is composed of a unidirectional LCMHS with four 90° turntables located at the corners, and *M* cells. Each cell has an entry (exit) point to (from) it called the loading (unloading) station. It is assumed that no cell is located between the turntables on the shorter sides of the LMCHS. The turntables are only activated when jobs need to (from) travel along the shorter sides of the conveyor.

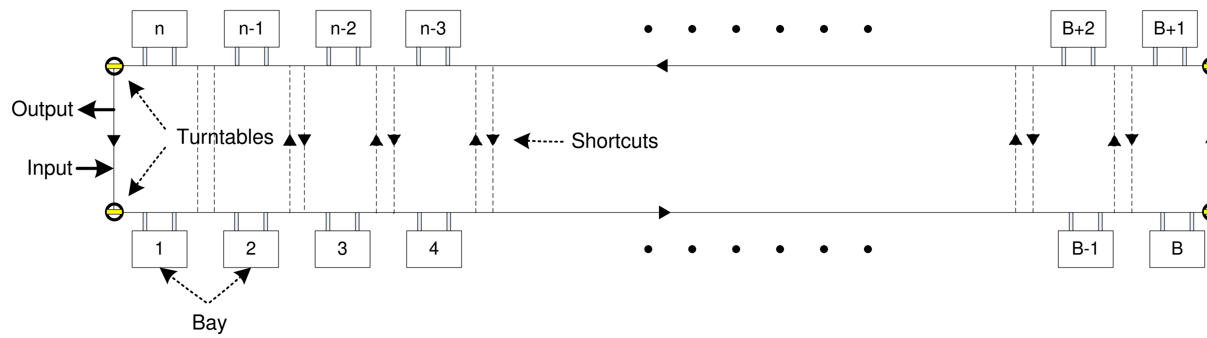

Figure 3.1: The LLMF with shortcuts

It is assumed that the loading and unloading stations at each cell have infinite capacity and are never blocked. Jobs in the facility will have associated routes which define the sequence of tools (and cells) a job needs to visit for processing. A job that completes processing in a particular cell is placed in the associated unloading station and waits to be loaded onto the LCMHS. The demand is modeled by using a "From-To" matrix representing the average flow rate of moves between a pair of cells i.e. λ_{ij}.

The LCMHS is specified in terms of its speed and length. The length can be described in terms of "windows". A window is defined to hold at most one job provided that all jobs have the same dimensions and all windows are of equal size. The conveyor cycle time is the time required for the conveyor to move the length of one window. It is assumed that the LCMHS load/unload time is constant and less than the conveyor cycle time and therefore the conveyor continues to move while loads are being loaded and unloaded from the load/unload stations.

The turntables are located at the points of intersection between various sections of the conveyor to change the load's traveling direction by 90 degrees. A turntable cycle consists of receiving a load, changing the load's direction, releasing the load, and returning to home position. The time to complete such cycle is assumed to be deterministic. It is also assumed that all turntables operate at the same speed.

It is important to note that if a shortcut is assigned after cell *i*, the flow of loads after the shortcut on the conveyor should be adjusted to reflect the amount of loads that are diverted on the shortcut *i*.

3.1.1 Phase I: The Traveling WIP on the Conveyor

Phase I analysis provides an estimate for the expected traveling WIP on the conveyor without considering any turntables as described in Bozer and Hsieh (2005). The conveyor travels at a constant speed; move requests follow a Poisson process; loading and unloading stations have unlimited capacity; and the conveyor is continuous with no turning delays (i.e. no turntables).

Consider that the conveyor is a series of nodes with a set of segments (*S*) connecting two nodes to form a network of nodes.

The turntable, loading station for cell 1, the unloading station for cell 1, the loading station for cell 2, the unloading station for cell 2, etc. are nodes, and only the sections of conveyor between adjacent nodes form the set of segments (S).

As defined earlier, a window (Υ) is the length of a conveyor defined to hold at most one job. Therefore, for a segment i with length d_i, the number of windows (w_i) is given by

$$w_i = \frac{d_i}{\Upsilon} . \tag{8}$$

Let α_i be the average number of loads per time unit on segment i and s be the distance based speed of the conveyor. The window based speed of the conveyor (v) with respect to the window size in terms of windows per time unit is given by

$$v = \frac{s}{\Upsilon} . \tag{9}$$

This representation of the window speed of the conveyor is general as it account for non-unity window sizes. As long as the conveyor system is stable as described in Bozer and Hsieh (2004); the probability that segment i is occupied (q_i) is given by

$$q_i = \frac{\alpha_i}{v} . \tag{10}$$

The expected traveling WIP (WIP_{PI}) on the conveyor is given by

$$WIP_{PI} = \sum_{i \in S} w_i q_i \ . \tag{11}$$

3.1.2 Phase II: WIP at the Turntables

In Phase II the turntables are analyzed in pairs by selecting the two corner turntables located at the same side of the conveyor. For each pair of turntables the downstream turntable will never have loads waiting in queue because both turntables have deterministic turning time and are synchronized.

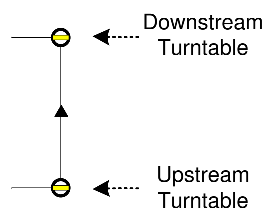

Figure 3.2: Types of Turntables

Queueing effects are only observed in the upstream turntable. Since it is assumed that jobs arrive according to a Poisson process, and the turning time is deterministic, the corner upstream turntable can be analyzed as an *M/D/1/b* system, where *b* is the number of windows separating the upstream turntable and the last unloading station before the turntable.

Let λ_C be the arrival rate of loads to the corner turntable, and t be the turning time of the turntable. Buzacott and Shanthikumar (1993) provide a thorough discussion of analyzing general blocking queues. The following approximation, which is also discussed by Hopp and Spearman (2000) is used to describe the expected WIP at the upstream turntable (WIP_U) which is given by:

$$WIP_U = \left(\frac{1}{2}\right)\left(\frac{\lambda_c^2 t^2}{1-\lambda_c t}\right) + \lambda_c t \;. \tag{12}$$

Equation (12) assumes that, on average, the turntable queue does not extend to block the pick-up station immediately upstream of the turntable which is considered as the stability condition. Details on verifying this stability condition are provided in Nazzal et al. (2008).

The expected WIP at the downstream turntable (WIP_D) would be its utilization and is given by

$$WIP_D = \lambda_c t \;. \tag{13}$$

Let λ_{rc} be the arrival rate of loads to the right corner turntable, and λ_{1c} be the arrival rate of loads to the left corner turntable. Therefore, the total WIP at the turntables (WIP_{II}) on the conveyor is given by

$$WIP_{PII} = \left[\left(\frac{1}{2}\right)\left(\frac{\left(\lambda_{rc} t\right)^2}{1-\lambda_{rc} t}\right) + 2\lambda_{rc} t\right] + \left[\left(\frac{1}{2}\right)\left(\frac{\left(\lambda_{lc} t\right)^2}{1-\lambda_{lc} t}\right) + 2\lambda_{lc} t\right]. \tag{14}$$

3.1.3 Phase III: WIP on the Shortcuts

In Phase *III*, the expected waiting delays and WIP resulting from shortcuts are incorporated. Consider the four stockers *p*, *q*, *r*, and *s* from Figure 3.3, and the shortcut turntables *e*, *f*, *g*, and *h*. A cell in this analysis is determined by four stockers and the insertion of two shortcuts, one in each direction. The reference for the cell is arbitrarily given to the lower left stocker, stocker *p* in this example. For any balanced system with *N* bays there will be a maximum of *B*−1 cells as shown in Figure 3.4.

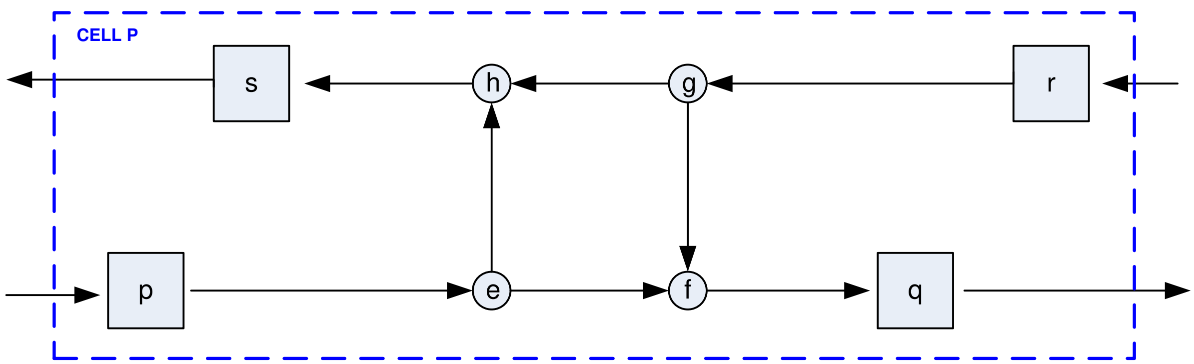

Figure 3.3: Cell *p*

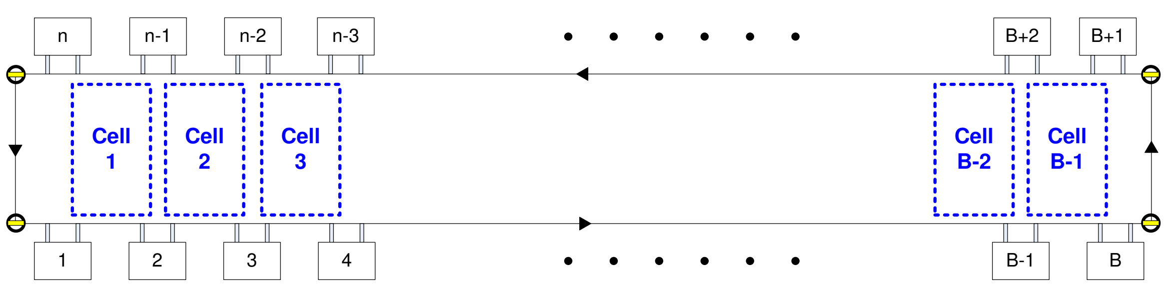

Figure 3.4: Cells in the LLMHS

The congestion caused by introducing shortcut *eh* and/or shortcut *gf* in cell '*p*' is now modeled. This is done by computing the average delays due to turntables. Let, T_e, T_g, T_f, and T_h be the expected delay at the queues that form due to turntables *e*, *g*, *f*, and *h*, respectively. It is assumed that the rate at which loads are picked off the CFT at stockers *s* and *q* is greater than the speed of the CFT, and therefore, no queue will form before either stocker. This assumption is consistent with the conveyor-based tool-to-tool model from SEMATECH (2002) as loads are removed from (moved to) the conveyor before being loaded (unloaded). In the SEMATECH Model, FOUPS are delayed due to loading and unloading at the stocker, without impacting the conveyor.

Further, no queue will form on shortcuts *eh* and *gf* for two reasons: 1) The deterministic and identical turning time of the turntables will ensure that the interarrival time of loads to segments *gf* and *eh* is always larger than the turning time of turntables *f* and *h,* respectively; 2) Higher priority at turntables *f* and *h* is given to the loads coming off shortcuts *gf* and *eh*, respectively.

The expressions to derive the mean arrival rate of loads on the shortcuts is first presented, namely λ_{eh} and λ_{gf}, and on other segments within a cell, namely λ_{ef} and λ_{gh}, given the from-to matrix of move requests. These expressions are necessary before deriving the analytical model for estimating the average delays and WIP caused by turntables *e* and *g*, and the model that estimates the average delays and WIP caused by turntables *f* and *h*.

3.1.3.1 Estimating the mean arrival rates of loads

3.1.3.1.1 Arrival rates of loads to shortcuts

It is assumed that turning loads arrive at turntables *g* and *e* according to a Poisson Process with arrival rate λ_{eh} and λ_{gf} respectively. λ_{ef} and λ_{gh} are estimated as the average number of loads per time that will require travel on, respectively, shortcuts *gf* and *eh* to take the shortest distance path from their origin stocker to their destination stocker. λ_{eh} values can be obtained by observing that the loads traveling on shortcut *eh* are those that originate from stockers upstream of turntable *e* for delivery to those downstream of turntable *h* minus the loads that would be carried on all the preceding cell shortcuts that have the same direction as *eh*.

$$\lambda_{eh} = \sum_{i=s+1}^{p} \sum_{j=s}^{i-1} \alpha_{ij} - \sum_{kl \in U_{eh}} \lambda_{kl} y_{kl} \ . \tag{15}$$

Similarly, values can be obtained by observing that the loads traveling on shortcut gf are those that originate from stockers upstream of turntable g for delivery to those downstream of turntable *f* minus the loads that would be carried on all the preceding cell shortcuts that have the same direction as *gf*.

$$\lambda_{gf} = \sum_{i=q+1}^{r} \sum_{j=q}^{i-1} \alpha_{ij} - \sum_{kl \in U_{gf}} \lambda_{kl} y_{kl} \ . \tag{16}$$

Where α_{ij} is the average rate of loads traveling from stocker i to stocker j, stocker $N+1$ is stocker 1, and, and U_{gf} (U_{eh}) is the set of shortcuts upstream of shortcuts gf (eh) and in the same direction. y_{kl} is an indicator variable that shortcut kl is installed (y_{kl} = 1), or not (y_{kl} = 0). Equations (15) and (16) are executed sequentially; equation (15) should be executed starting at cell 1 followed by cell 2 and so forth up to cell $B-1$. Equation (16) should be executed in the opposite direction; starting at cell $B-1$ and moving backwards down to cell 1.

3.1.3.1.2 Arrival rates of loads to segments between shortcuts

It is assumed that *passing* loads arrive at turntables e and g according to a Poisson process with arrival rates λ_{eh} and λ_{gf}, respectively. λ_{eh} are estimated as the average number of loads per time that will travel from stockers s, $s+1,\ldots, p$ to stockers q, $q+1, \ldots, r$. Also, if shortcut gf was not installed- all the loads that would have traveled on shortcut gf.

$$\lambda_{ef} = \sum_{i=s}^{p} \sum_{j=q}^{r} \alpha_{ij} + \lambda_{gf} (1 - y_{gf}) \ . \tag{17}$$

Similarly, arrival rates λ_{gh} are determined by estimating the average number of loads per time that will travel from stockers q, $q+1,\ldots,r$ to stockers s, $s+1$, …, p. Also, if shortcut eh was not installed – all the loads that would have traveled on shortcut *eh*.

$$\lambda_{gh} = \sum_{i=q}^{r} \sum_{j=s}^{p} \alpha_{ij} + \lambda_{eh}(1 - y_{eh}) \ . \tag{18}$$

3.1.3.2 Estimating the average WIP at input turntable of a cell

The congestion delays on segments *rg* and *pe* can be modeled as a single-server queue with two types of customers: turning loads and passing loads. The time for turning loads to be "served" at the turntable is modeled as a deterministic delay with mean *t*. Deterministic turning time is a reasonable assumption in a highly automated system and has been verified through consultation with industry collaborators. Passing loads require "no service" at a turntable but must wait to pass until there are no turning loads in front of them.

For turntable *e*, consider an M/D/l queue with arrival rate ($\lambda_{pe} = \lambda_{eh} + \lambda_{ef}$) and service time distribution:

$$S = \begin{cases} t & \text{for a turning load} \\ 0 & \text{for a passing load} \end{cases} . \tag{19}$$

$$\begin{aligned} E(S) &= E(S \,|\, \text{load is serviced}) \ \Pr(\text{load is serviced}) \\ &\quad + E(S \,|\, \text{load is passing}) \ \Pr(\text{load is passing}) \ . \\ &= t.\frac{\lambda_{eh}}{\lambda_{pe}} + 0.\frac{\lambda_{ef}}{\lambda_{pe}} \end{aligned} \tag{20}$$

Where $\lambda_{eh}/\lambda_{pe}$ is the steady-state probability that a load arriving at turntable *e* will turn to go on shortcut *eh*, *t* is the time for the turntable to rotate the load 90 degrees, wait for the load to get off the turntable, and turn back 90 degrees to the original position. The variance of *t* is zero, because turning times are deterministic.

By the Pollaczek-Khintchine formula (Khintchine, 1932; Pollaczek, 1930), the expected WIP, L_e, due to turntable *e*, is given by:

$$\begin{aligned} L_e &= \frac{\lambda_{pe}{}^2 E(S^2)}{2(1-\lambda_{pe}E(S))} + \lambda_{pe}E(S) \\ &= \frac{\lambda_{pe}\lambda_{eh}t^2}{2(1-\lambda_{eh}t)} + \lambda_{eh}t \end{aligned} \quad . \tag{21}$$

The analysis of turntable *g* will be identical after replacing *pe, ef,* and *eh* in equations (28)-(31) with *rg, gh, and gf*, respectively.

3.1.3.3 Estimating the average delays at the exit turntable of a cell

Loads traveling on segments *ef* and *gh* are passing loads that will get delayed by the loads coming from shortcuts *gf* and *eh*, respectively. Because the turning time of all turntables is deterministic, the minimum interarrival time to turntables *f* and *h* from the shortcut (by the turning loads) is *t*, the turning delay. Therefore, the passing loads on segments *ef* and *gh* will wait between 0 and *t* depending on the probability of finding the turntable occupied by a turning load (utilization of the turntable) and the remaining turning time for the load blocking their way. The average *remaining* service time, $E(t_r)$, of a turning load as seen by a randomly arriving passing load is given by (Kleinrock, 1975):

$$E(t_r) = \frac{t(c_s^2+1)}{2}\ . \tag{22}$$

Where, c_s^2 is the coefficient of variation of turning time. Since turning times are deterministic, $c_s^2 = 0$ and thus, $E(t_r)=t/2$. The expected service (busy) time of turntable *f*, is the proportion of loads that turn multiplied by the turning time. Therefore, the expected delay caused by turntable f is given by:

$$\begin{aligned} T_f &= u_f \frac{t}{2} + \frac{\lambda_{gf}}{\lambda_{ef}+\lambda_{gf}} t \\ &= \frac{\lambda_{gf} t^2}{2} + \frac{\lambda_{gf}}{\lambda_{ef}+\lambda_{gf}} t \end{aligned}\ . \tag{23}$$

The first term in expression (9) is the remaining turning time as seen by a load arriving from segment *ef*. The second term is the expected busy time of turntable *f*. U_f is the utilizations of turntable *f*. Therefore, using Little's law, the expected WIP due to turntable *f* is given by:

$$L_f = \lambda_{gf}\frac{\lambda_{gf}t^2}{2} + u_f$$
$$= \frac{\lambda_{gf}^2 t^2}{2} + \lambda_{gf}t \quad . \qquad (24)$$

The analysis of turntable *h* to estimate T_g and L_g will be identical after replacing subscripts *gf, ef, and f,* in equations (23) and (24) with *eh, gh, and g*, respectively.

3.1.4 WIP on the Conveyor

From equation (11) and equation (14) the estimated WIP on the conveyor (WIP_{CONV}) is given by

$$E(WIP_{CONV}) = \underbrace{\sum_{i \in S} w_i q_i}_{\text{Phase I: travelling WIP}} + \underbrace{\left(\frac{1}{2}\right)\left(\frac{(\lambda_{rc}t)^2}{1-\lambda_{rc}t}\right) + 2\lambda_{rc}t}_{\text{Phase II: two right corner turntables}} + \underbrace{\left(\frac{1}{2}\right)\left(\frac{(\lambda_{lc}t)^2}{1-\lambda_{lc}t}\right) + 2\lambda_{lc}t}_{\text{Phase II: two left corner turntables}}$$
$$+ \underbrace{\sum_{\forall (p,e,f,g) \in M-1} L_e y_{eh} + L_g y_{gf} + L_f y_{gf} + L_h y_{eh}}_{\text{accumulated WIP due to turntables } e,g,f,h \text{ in each cell}} \qquad (25)$$

3.1.5 Stability Condition for LLMF

For a LCMHS, the utilization is given by

$$\rho_{LCMHS} = \max_i \left[\frac{\lambda_i + \alpha_i}{v}\right] \qquad (26)$$

As long as $\rho_{LCMHS} < 1$, the LLMF is stable.

3.2 Input Station Analysis

3.2.1 Previous Models of WIP at the Input (Loading) Stations

3.2.1.1 Method of Atmaca (1994)

For each cell *i*, the WIP at the input stations is given by

$$E\left(WIP_{INP}\right)_i = \frac{\left(\nu - \alpha_i\right)\left(\nu - q_i\alpha_i + 2\alpha_i\right)}{2\nu^2\left(1 - q_i\right)\left(\nu - \alpha_i - \lambda_i\right)} \tag{27}$$

3.2.1.2 Method of Bozer and Hsieh (2004)

For each cell *i*, let γ_i represent the event that the queue at loading station is empty, therefore $P(\gamma_i)$ is given by

$$P\left(\gamma_i\right) = \frac{\lambda_i}{\nu - \alpha_i}. \tag{28}$$

Let a_i be the adjusted probability that segment *i* is occupied taking into account the correlation between the status of adjacent windows, a_i is given by

$$a_i = \frac{\overline{a}_i}{q_i} \tag{29}$$

where

$$\begin{aligned}\overline{a}_{i+1} = \overline{a}_i &+ \left(q_i - \overline{a}_i\right)\left\{P\left(\gamma_i\right) + \left(1 - P\left(\gamma_i\right)\right)F_i\left(1/\nu\right)\right\} \\ &+ \left(q_i - \overline{a}_i\right)P\left(\gamma_i\right) \\ &+ \left(\overline{a}_i - 2q_i + 1\right)\left\{P\left(\gamma_i\right) - \left(1 - P\left(\gamma_i\right)\right)F_i\left(1/\nu\right)\right\}\end{aligned} \tag{30}$$

and, F_i is exponentially distributed with rate λ_i. Bozer and Hsieh (2004) utilize the tagged load approach to estimate $E(WIP_{INP})_i$, also Bozer and Hsieh (2004) is restricted to loading stations with single robots. For each cell i, the expected WIP at the loading station is given by

$$E\left(WIP_{INP}\right)_i = \frac{\left(\nu - \alpha_i\right)\left(\nu - a_i\alpha_i + 2\alpha_i\right)}{2\nu^2\left(1 - a_i\right)\left(\nu - \alpha_i - \lambda_i\right)} \tag{31}$$

3.2.2 Proposed Methodology for WIP at Input Stations

The proposed methodology models the loading station as a M/G/1 queue. In general, the service time is the amount of time the load waits at the front of the queue, i.e. the head of the line (HOL), before it is loaded on the conveyor. It is assumed that the time the robot takes to transfer the load to the conveyor is negligible in comparison to the conveyor cycle time; defined as the time to move one window. Each load at the loading station will be served for either a Type 1 or a Type 2 service distribution.

3.2.2.1 Type 1 Service Distribution

This type of service time is when the load arrives to an empty input station queue

- Event 1: The load waits for the residual conveyor cycle time

- The Uniform Distribution with the range $[0,1/\nu]$ is used to model event 1

- Event 2: The load waits for the first unoccupied window
  - The Geometric distribution with probability of success $1 - \phi_i$ (ϕ_i further discussed in § 3.2.2.4 on page 68) is used to model the expected number of windows till the first empty window. This multiplied by the conveyor cycle time is used to model event 2

Both the events are assumed to be independent of each other

For each cell i, the expected service time for service type 1, $E(ST1_i)$, is given by

$$E\left[ST1_i\right] = \frac{1}{2v} + \frac{\phi_i}{1 - \phi_i} \cdot \frac{1}{v} \tag{32}$$

For each cell i, the variance for service type 1, $Var(ST1_i)$, is given by

$$Var\left[ST1_i\right] = \frac{1}{12v^2} + \frac{\phi_i}{\left(1-\phi_i\right)^2} \cdot \frac{1}{v^2} \tag{33}$$

3.2.2.2 Type 2 Service Distribution

This type of service time is when the load arrives to a non-empty input station queue

- Event 1: The load waits for the first unoccupied window

- The Geometric distribution with probability ϕ_i multiplied by the cycle time is used to model event 1

For each cell i, the expected service time for service type 2, $E(ST2_i)$, is given by

$$E\left[ST2_i\right] = \frac{\phi_i}{1-\phi_i} \cdot \frac{1}{v} \tag{34}$$

For each cell i, the variance for service type 2, $Var(ST2_i)$, is given by

$$Var\left[ST2_i\right] = \frac{\phi_i}{\left(1-\phi_i\right)^2} \cdot \frac{1}{v^2} \tag{35}$$

3.2.2.3 Expected WIP at input stations

For each cell *i*, the WIP at the input stations as per Welch (1964) is given by

$$\begin{aligned} E\left(WIP\right)_i = & \frac{\lambda_i E\left[ST2_i\right]}{1-\lambda_i\left[E\left[ST2_i\right]-E\left[ST1_i\right]\right]} \\ & + \frac{\lambda_i^2\left[Var\left[ST1_i\right]+E\left[ST1_i\right]^2-\left(Var\left[ST2_i\right]+E\left[ST2_i\right]^2\right)\right]}{2\left\{1-\lambda_i\left[E\left[ST2_i\right]-E\left[ST1_i\right]\right]\right\}} \\ & + \frac{\lambda_i^2\left[Var\left[ST2_i\right]+E\left[ST2_i\right]^2\right]}{2\left\{1-\lambda_i E\left[ST2_i\right]\right\}} \end{aligned} \tag{36}$$

Substituting equations (32)-(35) in equation (36), we get

$$E\left(WIP_{INP}\right)_i = \frac{2\lambda_i\phi_i}{\left(2v+\lambda_i\right)\left(1-\phi_i\right)} + \frac{\lambda_i^2\left(1+\phi_i-2\phi_i^2\right)}{3v\left(2v+\lambda_i\right)\left(1-\phi_i\right)^2} + \frac{\lambda_i^2\left(\phi_i+\phi_i^2\right)}{2v\left[v-\phi_i\left(v+\lambda_i\right)\right]\left(1-\phi_i\right)} \tag{37}$$

3.2.2.4 A note on the adjusted probability

The adjusted probability ϕ_i is the probability that a load arriving to the input station in segment i sees an occupied window. ϕ_i is developed using numerical experiments, in a manner similar to which the G/G/1 approximation, as presented by Kraemer and Langenbach-Belz (1976) and reported by Shanthikumar and Buzacott (1980), was developed.

It is observed that using the probability that the segment was occupied, i.e. q_i, as the probability of success for the Geometric distribution underestimated the number of Bernoulli trials until the first success. It is also observed that under high utilization, the adjustment required to q_i is minimal, whereas under low utilization the adjustment to q_i is significant. Intuitively, under high utilization, since the conveyor is almost completely occupied q_i approaches ϕ_i, and theoretically at a utilization of 1, $q_i = \phi_i$. With this in mind, for each cell i, a simple metric for ϕ_i is given by

$$\phi_i = q_i\left(2-\rho_i\right) \tag{38}$$

Where, the utilization for each cell i is given by

$$\rho_i = \frac{\lambda_i + \alpha_i}{v} \tag{39}$$

As it can be seen, equation (38) satisfies all the observances described above: under low utilizations the adjustment factor is significant, under high utilizations the adjustment factor is minimal, and when ρ_i is 1, $q_i = \phi_i$.

3.2.3 Total WIP at the Input stations

For the LCMHS, given $E(WIP_{INP})_i$, the total WIP $E(WIP_{INP})$ at the input stations is given by

$$E(WIP_{INP}) = \sum_{i=1}^{M} E(WIP_{INP})_i \tag{40}$$

3.3 Optimization Model

If the total WIP is used as the objective function of the LLDP, there is no penalty for adding shortcuts to the LLMF since adding shortcuts always reduces the WIP on the LLMF. Hence, the total cost function is used as the objective function of the LLDP as the total cost function enables the penalization of adding shortcuts to the LLMF. The total cost function is given by

$$Z = C_{WIP}\left[E(WIP_{INP}) + E(WIP_{CONV})\right] + C_{sc} \cdot \#Shortcuts \tag{41}$$

Let Ω be the ratio of the cost of installing the shortcut to the cost of a single unit of production. The effective cost per production unit is given by Hong et al. (2011) as follows

$$x = E\left(WIP_{INP}\right) + E\left(WIP_{CONV}\right) + \Omega \cdot \#Shortcuts \tag{42}$$

This method is employed to bypass the issue of determining the price of a unit of production and the price of installing a shortcut.

For a LLMF, the LLDP with a LCMHS is presented below using the formulation by permutations: the objective function as shown in equation (43) represents the total cost in the system for a permutation π. Equation (44) is included to ensure only feasible permutations if the LLMF are considered to solve the LLDP.

$$\underset{\pi \in S_N}{\text{Min}} \quad C_{WIP}\left[E\left(WIP_{INP}\right) + E\left(WIP_{CONV}\right)\right] + C_{sc} \cdot \#Shortcuts \,\big|_{\pi} \tag{43}$$

$$\text{s.t.} \quad \rho_{LCMHS_{\pi}} < 1 \tag{44}$$

3.3.1 The case for the use of genetic algorithms

Exact solution and heuristic methods cannot be used to solve the LLDP as presented. The lower bound techniques used to efficiently eliminate solutions by selective enumeration are invalid as they are built on the assumption that all the objective coefficients are known and unchanging. The coefficients of the objective function as presented in equation (43) are not known and vary stochastically at each iteration, as a result of the procedure used to estimate the WIP as presented in § 3. Therefore, the GA solution procedure is used to determine the near optimal (since there is no definite proof for convergence) solutions for the LLDP. § 4 will present the implementation of the proposed research design as described in § 3.

4 SOLUTION ALGORITHM FOR THE LLDP

The section discusses in some detail the implementation of the proposed research. The majority of the section discusses the solution algorithm for the LLDP.

The goals of this implementation are to highlight the benefit of using the WIP as opposed to distance traveled as the design criterion for the LLDP, and to also highlight the benefit of combining the determination of the Layout and the determination of the shortcuts into a single step LLDP as opposed to the two-step process as discussed previously.

A genetic algorithm (GA) is used to solve the LLDP as described in equation (43) and equation (44). Each permutation π represents a unique layout. In essence, for each permutation π, the greedy heuristic as described by Johnson et al. (2009) is used to determine the number of shortcuts. In this manner, the fitness value (equation (43)) for each and every permutation π reflects the benefit (if any) of including the shortcuts. The method to pick the best set of shortcuts is discussed in great detail in § 4.2.3 on page 83. As a result, the GA returns the solution that reflects the lowest WIP while considering shortcuts. Traditionally, one would first run a solution algorithm to determine the best layout, and then one would run another solution algorithm to determine the best set of shortcuts.

Thereby, the benefits of the shortcuts are only seen for the best layout. However, in the proposed methodology the benefits of the shortcuts are seen for every layout encountered, thereby guaranteeing an equivalent or better solution as compared to the traditional method.

4.1 Encoding the Chromosomes

4.1.1 Encoding the Cells: cell chromosomes

Haupt and Haupt (2004) is used as a reference for this following discussion. Consider the facility below:

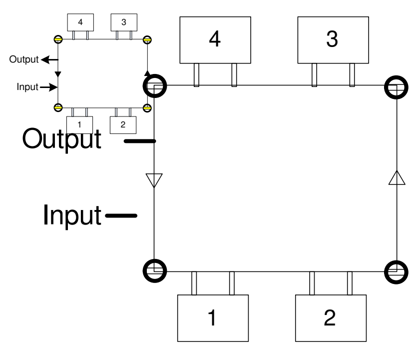

Figure 4.1: Illustrative Facility

There are four locations (N=4) and four machines (M=4). In the case as shown in Figure 4.1: machine 1 is in location 1, machine 2 is in location 2, etc. To generalize, each location is fixed while the cells are assigned to different locations. In terms of problem representation, the chromosomes will be encoded in a similar manner. The choice of the numbering of the locations and cells is arbitrary and selected by the practitioner.

$$\textit{cell chromosome} = \underbrace{m_1}_{1}\ \underbrace{m_2}_{2}\ \underbrace{m_3}_{3} \cdots \underbrace{m_M}_{N} = \left[m_1 m_2 m_3 \ldots m_M\right]$$

Here, m_i indicates a specific cell i represented by a floating-point number assign to a specific location (1,2,…,N). The general cell chromosome would read as follows: cell 1 is assigned to location 1, cell 2 is assigned to location 2, etc. Coming back to the illustrative problem, the cell chromosome for the Layout as depicted in Figure 3.1 is [1234].

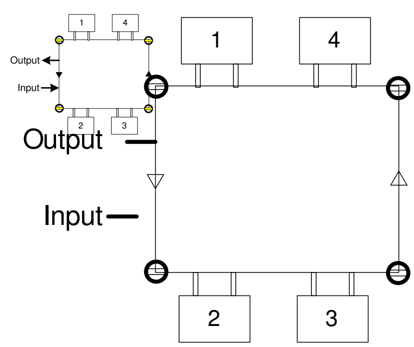

Figure 4.2: Alternate illustrative Facility

Likewise, the cell chromosome for the facility as shown in Figure 4.2 is [2341]. Hence, it can be seen that the reordering the numbers in a cell chromosome will result in different layouts. For the problem as depicted by Figure 4.1 and Figure 4.2, each cell *i* is represented by a single bit as N is a single bit. To further generalize, the number of bits for each cell should be derived from the number of bits required to represent N. Table

4.1 illustrates the number of bits required to encode each cell with respect to N.

Table 4.1: Number of bits required for different N's

N	Bits
1-9	1
10-99	2
100-999	3
1000-9999	4
⋮	⋮

To further illustrate this, consider the facility in the Figure 3.3, machine 1 is in location 1, machine 2 is in location 2, etc. N is in between 10 and 99, therefore two bits will be required to encode each machine.

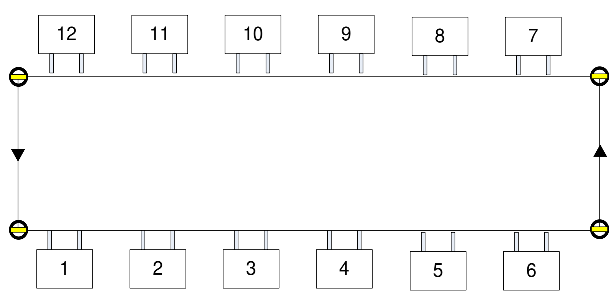

Figure 4.3: Alternate illustrative Facility

The cell chromosome for the facility in Figure 4.3 is

$$Chromosome = [010203040506070809101112]$$

Likewise, for Figure 4.4 the cell chromosome is [090207060504030801121110]

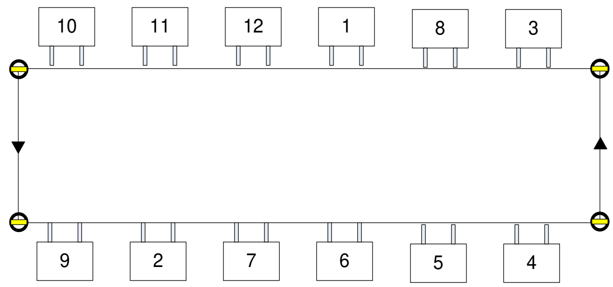

Figure 4.4: Alternate illustrative Facility

4.1.2 Encoding the Shortcuts: shortcut chromosomes

If a shortcut is assigned after a cell i then it will be encoded as 1, else 0. Consider the facility below

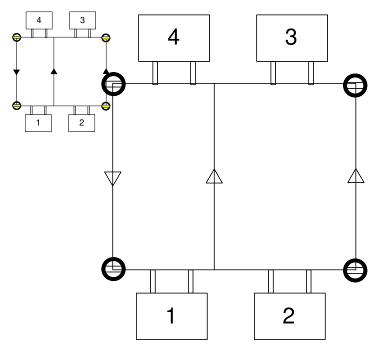

Figure 4.5: Illustrative Facility with shortcuts

As illustrated by Figure 4.5, there is a shortcut after cell 1, cell 2, and cell 4. There is no shortcut after cell 3. Therefore, the shortcut chromosome for this Layout can be encoded as follows: [1101]. It is important to note that if a cell is the last cell on its side of the conveyor in the direction of flow, then a shortcut is always placed after that cell (the short wall of the conveyor that connects the two sides.)

4.1.3 Encoding a Layout or permutation π

Combining the method for encoding the cells and the shortcuts, the Layout and shortcut configuration as shown Figure 4.5 can be represented as: [1234][1101]. The first part represents the chromosome for the cells henceforth referred to as the cell chromosome, while the second part represents the chromosome for the shortcuts henceforth referred to as the shortcut chromosome, and both together represent the chromosome for the permutation π. The method to generate the chromosome for the cell is described in § 4.2.2 on page 83. The method to generate chromosome for the shortcuts is described in § 4.2.3 on page 83. This particular configuration will yield its corresponding WIP which will be used as the fitness function for the GA.

4.2 High Level Solution Algorithm

The flowchart of the solution algorithm is presented in Figure 4.6. Each sub task is presented subsequently in their respective sections.

In essence, the GA is initialized after which an initial population of cell chromosomes is generated. Next, the fitness value for the permutation π as given by equation (42) is computed. For each permutation π, there is a set of shortcuts as represented by the shortcut chromosome that minimizes the WIP for the respective cell chromosome. In this way, the proposed methodology improves on the traditional two-step process of the Layout by finding the best set of shortcuts at each iteration for every Layout arrangement (cell chromosome) visited.

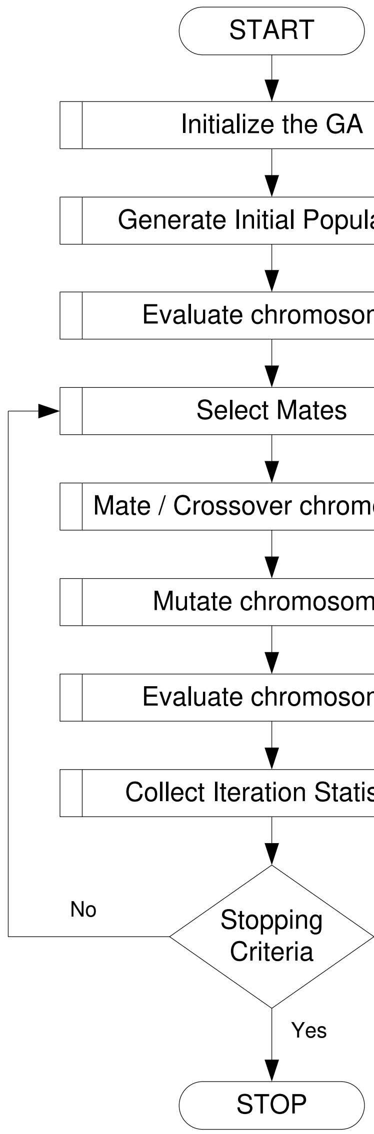

Figure 4.6: Flowchart of Solution Algorithm

After the fitness value is computed for all the permutations, the population is ordered from least fitness value to largest fitness value. A certain number of permutations (selection rate * population) are retained, the rest are discarded. After this point the GA loop begins.

The mates are selected using tournament selection and enough offspring are generated so that the population size is the same as before. Next, the cell chromosomes are mutated and then each permutation π is reevaluated just as described earlier. Next the iteration statistics are collected. The GA loops till the stopping criterion is reached.

4.2.1 Initializing the GA

In this sub-process, all the parameters of the GA are set. The process is fairly straight forward; the user enters the requisite information for the parameters of the GA.

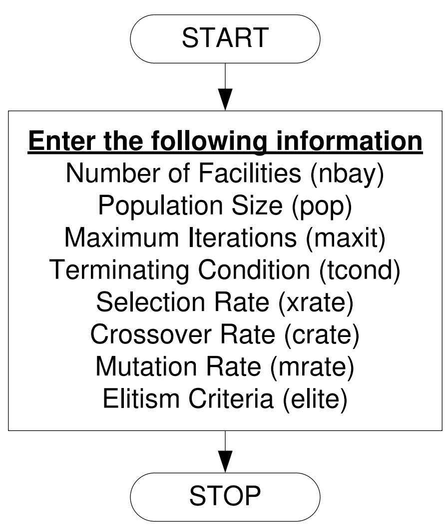

Figure 4.7: Flowchart of the Initialize Sub-process

The user also enters information about the LLMF, so as to evaluate the fitness function, viz. the ratio of the cost to install a shortcut to the cost of a unit of production from equation (42), the flow rate multiplier from equation (45), and the speed of the conveyor.

4.2.1.1 A note on Initial Parameter selection

Haupt and Haupt (2004) is used as a reference for this discussion. Proper initial parameter selection can ensure the quality of the solution. The approaches discussed obtain their inferences by analyzing a variety of GAs generated by varying μ, N_{pop}, X_{rate}, and G. μ is the mutation rate, N_{pop} is the number of chromosomes, X_{rate} is the crossover rate, G is the generation gap and has the bounds $0 < G \leq 1$. The generation gap, G, is the fraction of the population that changes every generation. A generation gap algorithm picks $G \cdot N_{pop}$ members for mating. The $G \cdot N_{pop}$ offspring produced replace $G \cdot N_{pop}$ chromosomes randomly selected from the population.

De Jong (1975) presents the following observations on choice of initial parameters:

f) Small population sizes improve initial performance

g) Large population sizes improve long-term performance

h) High mutation rates are good for off-line performance, where off-line performance is the running average of the best cost solution found in each generation

i) Low mutation rates are good for on-line performance, where on-line performance is the running average of all cost solutions up to the current generation

j) Crossover rate should be around 0.60

Grefenstette (1986) is uses a meta-genetic algorithm to optimize the on-line and off-line performance of GAs. He suggests that, "while it is possible to optimize GA control parameters, very good performance can be obtained with a range of GA control parameter settings." Schaffer, Caruana, Eshelman, and Das (1989) tests 8400 possible combinations of GAs and report the best on-line performance resulted for the following parameter settings: $\mu = 0.005$ to 0.01, $N_{pop} = 20$ to 30, and $X_{rate} = 0.75$ to 0.95.

Bäck (1993) shows that the desirable mutation rate $\mu = 1 / N_{bits}$, where N_{bits} is the number of bits of the chromosome. Gao (1998) computes a theoretical upper bound on convergence rates in terms of μ, N_{pop}, and N_{bits} by developing a Markov chain model for the canonical GA. The resulting theorem shows that GAs converge faster for large μ and smaller N_{pop}. Cervantes and Stephens (2006) state that using $1/N_{bits}$ too general and that one can generally choose $\mu \ll 1/N_{bits}$.

Traditionally large populations have been used to thoroughly explore complicated cost surfaces. Crossover rate is the operator of choice to exploit those solution spaces; the role of mutation is somewhat nebulous. In one sense, greater exploration is achieved if the mutation rate is great enough to take the gene into a different region of solution space. Yet a mutation in the less critical genes may result in further exploiting the current region. Perhaps the larger mutation rates combined with the lower population sizes act to cover both properties without the large number of function evaluations required for large population sizes.

Haupt and Haupt (2004) have performed extensive comparisons of GA performance as a function of population size and mutation rate, as well as some other parameters. The criterion was finding a correct answer with as few evaluations of the cost function as possible. Their conclusions are that the crossover rate, method of selection (roulette wheel, tournament, etc.), and type of crossover are not of much importance. Population size and mutation rate, however, have a significant impact on the ability of the GA to find an acceptable minimum.

4.2.2 Generate Initial Population and Cell Chromosome

The initial population of cell chromosomes can be generated using the Fisher-Yates shuffle algorithm (Fisher & Yates, 1948). The algorithm is as follows:

```
Step 0: Set initial chromosome to a sequential ordering of N fa-
        cilities to current chromosome
Step 1: Set N = number of facilities
Step 2: Set i = N
Step 3: Set j = random integer such that 1 ≤ j ≤ i
Step 4: Swap the values in the ith and jth position of current
        chromosome
Step 5: Set i = i-1 and repeat step 3 until i=2, then STOP
```

This algorithm is applied 'p' number of times (to generate p chromosomes) where p is the desired population.

4.2.3 Evaluate Permutation π

This is the most computationally expensive step of the GA. In an attempt to expedite the evaluation of each permutation π, a table of solutions is maintained. The table contains three columns of information: Cell chromosome, shortcut chromosome, and fitness value. As the GA progresses, the table is appended with new permutations that are encountered.

For each permutation π in the population, the evaluation procedure is as follows: Search for the cell chromosome in first column of the table, if it is found then return the shortcut chromosome and fitness value, else a corresponding shortcut chromosome is generated and in the process the fitness value for the permutation π is computed using equation (42). The table is then updated with the information of the new permutation π.

4.2.3.1 GA applied to solve only the layout problem

If the GA is applied to solve only the layout problem then method as prescribed by § 4.2.3.1 for determining the shortcuts is omitted in the operation of the GA. In this manner, the GA will solve for a system that determines only the layout of the LLMF.

4.2.3.2 Generating the shortcut chromosome

Johnson et al. (2009) prescribes a greedy heuristic to identify the best set of shortcuts for a given cell chromosome. The heuristic is as follows:

```
Step 0: Start without any shortcuts
Step 1: Using the equation (42),i.e. the fitness value, evaluate
        the effect of adding each shortcut individually
Step 2: Rank shortcuts according to their impact on fitness val-
        ue (the higher the rank the greater the effect in de-
        creasing the WIP)
Step 3: Add highest ranked remaining shortcut. If the fitness
        value decreases; go to Step 4, otherwise stop
Step 4: Add shortcut to set of best shortcuts, return to Step 3.
```

Use encoding procedure as described in § 4.1.2 to generate the shortcut chromosome. Next, record the resulting fitness value for the current permutation π.

4.2.4 Select Cell Chromosomes for Mating

After evaluating the population, the permutations are ranked. The highest rank has the lowest fitness value. A portion of the population (selection rate * population) is selected for mating, the rest are discarded. Tournament selection is used to select the pairs of cell chromosomes from the retained permutations for mating.

4.2.5 Mate / Crossover Cell Chromosomes

Two cell chromosomes are mated to create a new offspring. The methodology is best illustrated by example. Consider a facility with 7 cells. The cell chromosomes for permutations are [1234567] and [7351264]. The crossover point (crossover rate * number of facilities) is the position in the cell chromosome over which the permutations swap values. Arbitrarily, the cross-over point is determined by rounding up the result of multiplying the crossover rate by the number of facilities by the number of bits required to represent the facilities to the next integer. For the current example: the number of facilities is 7; the number of bits required is 1; and if the crossover rate is 0.4, the crossover point is the 3. The first step of the mating results in the following children (the parents are split at the crossover point). The second portion of parent 2 (parent 1) is appended to the first portion of parent 1 (parent 2) to form Child 1 (child 2) as illustrated below:

Parent 1 = [123|4567] → Child 1 = [123|1264]

Parent 2 = [735|1264] → Child 2 = [735|4567]

As it can be seen, Child 1 and Child 2 are not unique permutations. The procedure described henceforth ensures unique offspring are created.

For Child 1 (Child 2), create three ordered sets of values:

- Set 1 → values from Child 1 (Child 2) that are before the crossover point
- Set 2 → values from Child 2 (Child 1) that are before the crossover point
- Set 3 → values from Child 1 (Child 2) that are after the crossover point
- For each value of Set 3
    - Check for value in Set 1
        - If found then replace value from Set 3 with corresponding value from Set 2 and repeat procedure for replaced value
        - If not found is Set 1, then move to next value in Set 3 otherwise restart procedure with current value

- After completion, append Set 3 to Set 1 to get a unique Child 1 (Child 2)

Coming back to the example, the procedure as described above is illustrated below, for Child 1:

Set 1 = [123]

Set 2 = [735]

Set 3 = [1264]

➔ The first value of Set 3 is '1', it is found in Set 1. The corresponding value for '1' from Set 1 in Set 2 is '7', so replace '1' in Set 3 with '7'. Set 3 is now [**7**264], '7' is not in Set 1, so move to next digit in Set 3.

➔ Next value in Set 3 is '2', it is found is Set 1, the corresponding value for '2' from Set 1 in Set 2 is '3', so replace '2' in Set 3 with '3'. Set 3 is now [7**3**64], '3' is in Set 1. The corresponding value for '3' from Set 1 in Set 2 is '5', so replace '3' in Set 1 with '5'. Set 3 is now [7**5**64], '5' is not in Set 1, so move to next digit in Set 3.

➔ Next value in Set 3 is '6', it is not found is Set 1, so move to next digit in Set 3. Set 3 is now [7**5**64].

➔ Next value in Set 3 is '4', it is not found is Set 1, so move to next digit in Set 3. Set 3 is now [7**5**64].

➔ There are no more digits in set 1,

→ Child 1 is now [1237564]

REPEAT PROCEDURE FOR CHILD 2.

4.2.6 Mutate Cell Chromosomes

Given the mutation rate, nmut (mutation rate * {population – 1} * number of facilities) mutations are performed. The methodology is as described below.

Step 1: Set counter to zero Step 2: if elitism in place: Set i = random integer such that $2 \le i \le pop$, otherwise $1 \le i \le pop$ Step 3: Set j = random integer such that $1 \le j \le nbay$ Step 3: Set k = random integer such that $1 \le k \le nbay$ Step 4: Go to row i in the population, swap the j^{th} and k^{th} values of the cell chromosome, while counter < nmut return to step 2 and increment counter by 1, otherwise STOP

4.2.7 Terminating Condition

As discussed in the previous sections, there is no proof for convergence for a GA, therefore some criteria has to be set on when to terminate the GA: usually referred to as a terminating condition. In the GA implemented, the terminating condition is set to the maximum number of iterations as set by the user. In the test problem, the terminating condition was 1000 iterations.

4.2.8 Collect Iteration Statistics

The permutation π with the best (lowest) fitness value from each iteration is recorded. These recorded fitness values are then plotted and analyzed to ensure the GA is performing adequately.

5 TESTING PROCEDURE

The objectives of this research are to propose the design of a LLMF with a LCMHS with shortcuts by minimizing the WIP in the system while using GAs to solve the LLDP. This chapter presents the tasks that are performed to support the research objectives. The three main tasks are:

1. Validate the proposed analytical approximation for the expected WIP at the input stations as given by equation (37) in § 3.2.2.3.
2. Test and evaluate the overall proposed methodology (LLDP) of Layout and shortcut design for a LLMF.
3. Determine the set of parameters that improve the performance of the genetic algorithm solution procedure by varying the parameters over an initial number of test problems. These parameters once determined will be fixed for all the problems tested.

5.1 Testing the Expected Value of WIP at the input Stations

This section presents the methodology for validating the expected value for the WIP at the input stations to a LCMHS with multiple input and output stations. For the expected WIP at the input stations: each of the system configurations presented will be simulated and the accuracy of the methodology to estimate the

WIP at the input stations will be evaluated. The simulation model as presented by SEMATECH (2002) is used to generate the simulation data against which the estimate for the WIP at the input stations will be tested. This simulation model has been tested, validated, and verified by academic and industrial professionals as being representative of a semiconductor manufacturing fab. Finally, various hypotheses are tested that compare the results of the total WIP at the input stations from the simulation against the analytical estimate using the Generalized Linear Model (GLM) analysis procedure with post-hoc analysis that enables the comparison of means from multiple groups while minimizing the Type I and Type II errors.

5.1.1 Problem Description

Consider a 24 cell LLMF as shown in Figure 5.1. This LLMF is a simplified depiction of a 300mm wafer fabrication facility as described in Agrawal and Heragu (2006), Nazzal and El-Nashar (2007), and SEMATECH (2002). The flow rates between the facilities are known and represented in the 'from-to' matrix (further described in § 5.1.2).

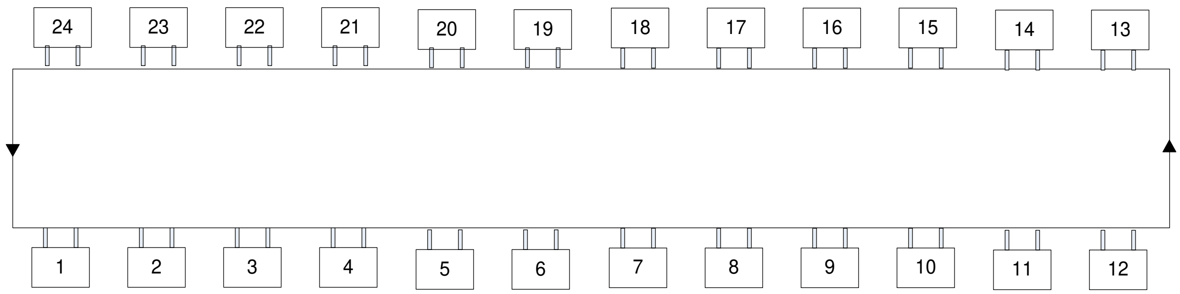

Figure 5.1: 300mm Wafer Fabrication Facility

5.1.2 Parameters to be varied

The parameters presented in Table 5.1 are varied to generate the different scenarios. As it can be seen, 90 different scenarios are considered. The simulation runs will be performed using Automod Simulation Software from Brooks Automation. Each simulation is warmed up for 2 days (simulation time) and then run for 10 replications of 30 days (simulation time). The total WIP at the input stations is captured for each replication. The speed of the conveyor is set to 3 ft/sec.

Table 5.1: Parameters to vary for testing the Expected total WIP at the Input stations

	Level					
Factor	1	2	3	4	5	6
Utilization (ρ_{LCMHS})	0.15	0.3	0.45	0.6	0.75	0.9
Job Flow Matrix (Layout)	X	Y	Z			
Arrival Process (c_a^2)	0.5	0.77	1	1.23	1.5	

It is important to notice that the conveyor speed and flow rate multiplier have not been included in the list of parameters to vary. Based on empirical observances, any combination of conveyor speed and flow rates that yields the same conveyor utilization, denoted by ρ_{LCMHS}, will have statistically indifferent results in terms of total WIP on the LCMHS; hence for a given layout it is sufficient to vary the utilization of the conveyor (ρ_{LCMHS}).

Different job flow matrixes are used to test different systems so as to introduce some diversity of flows into the testing procedure. For each flow layout l, at a specified conveyor utilization, the effective flow rates (λ_{ij}) can be generated using an arrival rate multiplier (ϑ_l) that adjusts the raw flow rate as given by.

$$\lambda_{ij} = \vartheta_l \cdot \tilde{\lambda}_{ij} \qquad (45)$$

Three layouts are utilized: Layout X, Layout Y, and Layout Z. The arrival rate multipliers are given in Table 5.2. The base flow rates matrix for Layout X is presented in Appendix A while the base flow rates matrix for Layout Y is presented in Appendix B. For Layout Z, all bays send the same number of loads to all other bays; the base flow rates matrix for the uniform layout is given by:

$$\tilde{\lambda}_{ij} = \begin{cases} 0 & \forall\ i = j \\ 0.5273 & \forall\ i \neq j \end{cases} \tag{46}$$

Table 5.2: Flow Rate Multipliers at different Conveyor Utilizations

	ρ_{LCMHS}					
ϑ	0.15	0.30	0.45	0.60	0.75	0.90
Θ_X	10.6410	21.2820	31.9230	42.5640	53.2050	63.8460
Θ_Y	7.0400	14.0790	21.1190	28.1590	35.1980	42.2380
Θ_Z	11.1320	22.2640	33.3960	44.5280	55.6600	66.7920

Note: The multipliers for the various layouts are selected such that the overall WIP for each layout is approximately the same at each level of utilization given a fixed conveyor speed 3 ft/sec for the different layouts

The squared coefficient of variation of the arrival process c_a^2 is varied because it is important to check how robust the methodology is with respect to different input arrival processes, so as to prescribe a general approach. The Weibull distribution is used to obtain the required variation in the arrival processes (c_a^2) for systems tested. It is represented by Weibull (β, α) as presented in Walck (2007); where α is the shape parameter, and β is the scale parameter. From Walck (2007), the mean (average) of Weibull (β, α) is given by

$$\mu = \frac{\beta}{\alpha}\Gamma\left[\frac{1}{\alpha}\right] \tag{47}$$

Where, $\Gamma[x]$ represents the gamma function. Next, from Walck (2007), the variance of Weibull (β, α) is given by

$$\sigma^2 = \frac{\beta^2}{\alpha}\left[\left(2\Gamma\left[\frac{2}{\alpha}\right]\right) - \left(\frac{1}{\alpha}\Gamma\left[\frac{1}{\alpha}\right]^2\right)\right] \quad (48)$$

Therefore the coefficient of variation for Weibull (β, α) is given by

$$c_a^2 = 2\alpha \frac{\Gamma[2/\alpha]}{\Gamma[1/\alpha]^2} \quad (49)$$

It is imperative that all the test levels have the same average effective flow while reflecting the various levels of variability. In order to achieve this, for each effective flow rate between cell *i* and cell *j*; the mean of the Weibull Distribution (μ_{ij}) is equal to the effective flow rate (λ_{ij}). Therefore, the scale parameter for the Weibull distribution (β_{ij}) can be represented as

$$\beta_{ij} = \mu_{ij}\frac{\alpha}{\Gamma[1/\alpha]} = \lambda_{ij}\frac{\alpha}{\Gamma[1/\alpha]} \quad (50)$$

As it can be seen, to determine β_{ij} the effective flow rate (λ_{ij}) between cell *i* and cell *j* in the LLMF multiplied by an adjustment factor (δ) which is given by

$$\delta = \frac{\alpha}{\Gamma[1/\alpha]} \quad (51)$$

As it can be seen in Table 5.3, the adjustment factor (δ) is given for each level of c_a^2 to ensure that the same average effective flow is observed at each level of variability. Next, the squared coefficient of variation for the Weibull distribution can be varied by changing α. Given equation (49), in Microsoft Excel one can use the solver tool to determine the values of α that yield the corresponding c_a^2 values. It is important to note that the values for the shape parameter (α) and the adjustment factor (δ) are general and can be applied to any family of Weibull distributions. The values for the shape parameter are as given in Table 5.3 .

Table 5.3: Parameters for Weibull Distribution

c_a^2	α	δ
0.5	1.435525	1.101
0.77	1.142287	1.049
1	1	1
1.23	0.903123	0.952
1.5	0.821714	0.899

5.1.3 Summary of Testing Procedure for WIP at Input Stations

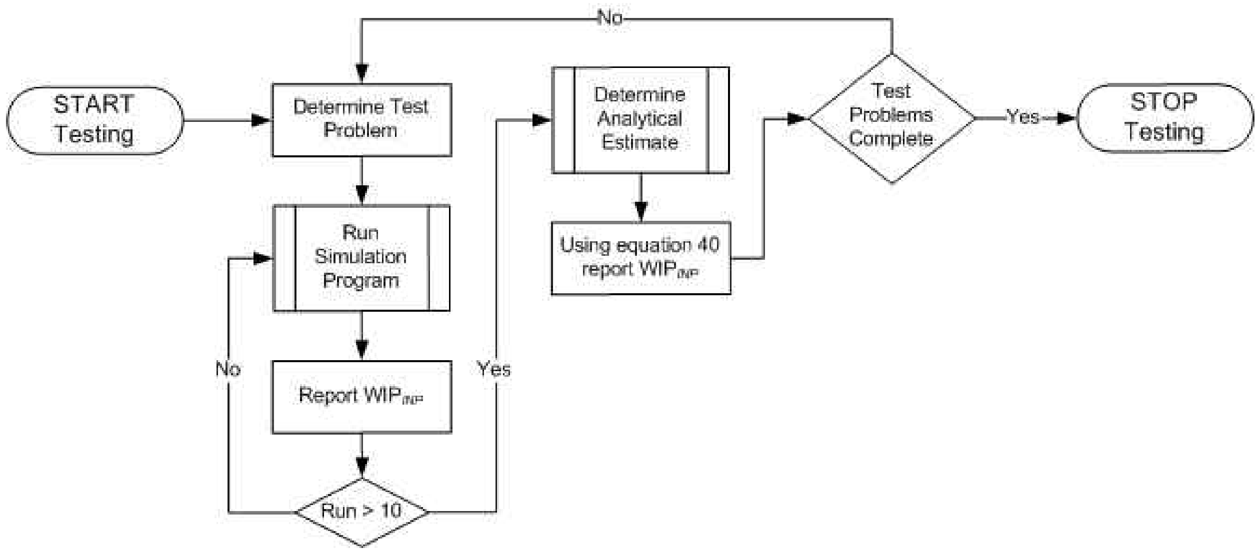

Figure 5.2: Summary of Testing Procedure

5.1.4 Method for Analysis of Test Data

A Generalized Linear Model (GLM) will be used to analyze the data collected from the testing. GLMs are powerful because they unify several statistical techniques under a single modeling paradigm. In the event of comparing means from multiple groups to each other, the use of any of the family of t-tests would lead to an increase in the Type 1 error (Roberts & Russo, 1999). GLMs enable comparing means from multiple groups to each other by incorporating post hoc analysis methods such as Tukey's Range Test (Tukey, 1977) that control for Type I error (McCulloch, Agarwal, & Neuhaus, 2008). As indicated by Day and Quinn (1989) and SAS Institute Inc (2010), the REGWQ multiple comparison procedure (Ryan, 1960) not only controls for Type I error but has a higher statistical power (i.e. lower Type II error) than the Tukey's Range Test. Hence, both procedures will be used to verify and validate the comparison of means results.

Gill (2000) and McCulloch, Agarwal, and Neuhaus (2008) both provide detailed descriptions of the GLM and attribute the development of the GLM to Nelder and Wedderburn (1972). The GLM procedure has the capability to perform many different statistical analyses, viz.: simple regression, multiple regression, ANOVA, analysis of covariance, response surface models, weighted regression, polynomial regression, partial correlation, MANOVA, and repeated measures ANOVA (SAS Institute Inc, 2010).

It is important to note that for each layout (A, B, and C) a separate GLM analysis will be performed. For the GLM, there are two types of input variables to be defined: the dependent variable(s), and the independent variable(s). In this case, the dependent variable is the total WIP at the input station (labeled WIP). The independent variables are the parameters that are varied: the utilization of the conveyor (ρ_{LCMHS}), and the coefficient of variation of the input arrival process (c_a^2). Another independent variable considered is an indicator variable (M) for the source of the total WIP at the input station, i.e. WIP from simulation or WIP from estimate, where 1 $\rightarrow$ WIP from simulation and 0 $\rightarrow$ WIP from estimate. Here, both REGWQ and Tukey's post hoc analysis methods can test the difference in the total WIP at the input stations for the levels of M, i.e., simulation vs. analytical.

Another independent variable (RHOM) considered an indicator variable introduced to capture the interaction of ρ_{LCMHS} and M. Since there are 6 levels of ρ_{LCMHS} and 2 levels of M, RHOM has 12 levels as illustrated in Table 5.4. At it can be seen, simulation values of the total WIP at the input stations are used when RHOM is odd while the analytical estimate of the total WIP at the input stations is used when RHOM is even.

Table 5.4: Description of RHOM

ρ_{LCMHS}	M	RHOM
0.15	1	1
0.15	0	2
0.3	1	3
0.3	0	4
0.45	1	5
0.45	0	6
0.6	1	7
0.6	0	8
0.75	1	9
0.75	0	10
0.9	1	11
0.9	0	12

In this manner, one can test the efficacy of the analytical estimate for different levels of ρ_{LCMHS}. To further elaborate, if there is no difference in the analytical estimate and the simulation values at a particular ρ_{LCMHS} then the Tukey's and REGWQ post hoc methods group the two as being statistically indifferent from each other.

Finally, another independent variable (SCVM) considered is an indicator variable introduced to capture the interaction of c_a^2 and M. Since there are 5 levels of c_a^2 and 2 levels of M, SCVM has 10 levels as illustrated in

Table 5.5. At it can be seen, simulation values of the total WIP at the input stations are used when SCVM is odd while the analytical estimate of the total WIP at the input stations is used when SCVM is even. Therefore, every even value of SCVM will have the same WIP as described by the analytical estimate.

In this manner, one can test the efficacy of the analytical estimate for different levels of c_a^2. More specifically, if there is no difference in the analytical estimate and the simulation values at a particular c_a^2 then the Tukey's and REGWQ post hoc methods group the two as being statistically indifferent from each other.

Table 5.5: Description of SCVM

c_a^2	M	SCVM
0.50	1	1
0.50	0	2
0.77	1	3
0.77	0	4
1.00	1	5
1.00	0	6
1.23	1	7
1.23	0	8
1.50	1	9
1.50	0	10

Note: M = 1 -> Simulation; M = 0 -> Analytical Estimate

To summarize, Table 5.6 presents the independent variables for the GLM procedure along with the different levels for each variable.

Table 5.6: Description of Independent Variables for GLM

Factor	Levels
Utilization (Conveyor)	(0.15, 0.30, 0.45, 0.60, 0.75, 0.90)
Arrival Process (SCV)	(0.50, 0.77, 1.00, 1.23, 1.50)
M	(0, 1)
RHOM	(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12)
SCVM	(1, 2, 3, 4, 5, 6, 7, 8, 9, 10)

Note: For each layout (X, Y, and Z) separate GLM analysis will be performed.

Table 5.7 presents an illustration (not actual test results) of a subset of the input data for the GLM. As it can be seen when M = 0 (analytical estimate), the 'Run' values are the same since the estimate for the total WIP at the input stations does not change. When M = 1 (simulation), the "Run" values vary as expected.

Table 5.7: Example of Subset of Total WIP at Input Stations Data table for GLM

						Run			
ρ_{LCMHS}	Layout	c_a^2	M	RHOM	SCVM	1	2	…	10
0.3	X	0.50	0	4	2	12.16	12.16	…	12.16
0.3	X	0.50	1	3	1	12.61	12.44	…	12.38
0.6	Z	1.00	0	8	6	15.24	15.24	…	15.24
0.6	Z	1.00	1	7	5	15.46	16.07	…	15.59
0.9	Y	1.50	0	12	10	39.44	39.44	…	39.44
0.9	Y	1.50	1	11	9	40.52	37.52	…	41.52

Note: This table is for illustrative purposes only.

5.1.5 Hypothesis

The total WIP at the input stations from the simulation is tested against the estimate of the total WIP at the input stations as given by equation (40) on page 69. This section describes the hypotheses that will be tested using the GLM procedure.

5.1.5.1 Hypothesis Test 1

This is the most general test of the accuracy of the proposed estimate of the total WIP over a variety of utilization levels and arrival distributions. The hypothesis is as follows:

$H1_0$ There is no statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

$H1_A$ There is a statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

In the event $H1_0$ is not accepted, four new hypotheses will be proposed and tested; the outcomes of which will serve to provide the operating conditions under which the estimate of the Total WIP at the input stations as given by equation (40) on page 69 are statistically indifferent from the total WIP at the input stations from the simulation.

5.1.5.2 Hypothesis Test 2

This hypothesis tests the levels of utilization over which the analytical estimate and the simulation output are statistically indifferent for all arrival distributions. The hypothesis is as follows:

$H2_0$ Given the utilization of the conveyor is within a specified range (to be determined in the analysis); there is no statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

$H2_A$ Given the utilization of the conveyor is within a specified range (to be determined in the analysis); there is a statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

5.1.5.3 Hypothesis Test 3

This hypothesis tests if the analytical estimate and the simulation output are statistically indifferent when the squared coefficient of variation of the arrival process is less than 1; for all levels of utilization. The hypothesis is as follows:

$H3_0$ Given the squared coefficient of variation of the arrival process is less than 1; there is no statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

$H3_A$ Given the squared coefficient of variation of the arrival process is less than 1; there is a statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

5.1.5.4 Hypothesis Test 4

This hypothesis tests if the analytical estimate and the simulation output are statistically indifferent when the squared coefficient of variation of the arrival process is 1; for all levels of utilization. The hypothesis is as follows:

$H4_0$ Given the squared coefficient of variation of the arrival process is 1; there is no statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

$H4_A$ Given the squared coefficient of variation of the arrival process is 1; there is a statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

5.1.5.5 Hypothesis Test 5

This hypothesis tests if the analytical estimate and the simulation output are statistically indifferent when the squared coefficient of variation of the arrival process is greater than 1; for all levels of utilization. The hypothesis is as follows:

$H5_0$ Given the squared coefficient of variation of the arrival process is greater than 1; there is no statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

$H5_A$ Given the squared coefficient of variation of the arrival process is greater than 1; there is a statistically significant difference between the mean total WIP at the input stations from simulation and the analytical estimate of mean total WIP at the input stations.

5.2 Testing the LLDP

The goal of testing the LLDP is to compare the proposed methodology of using the *WIP* as the design criterion while *combining* the Layout and shortcut solution procedures, against using the total *distance* travelled as the design criterion to first solve the LLDP and then another algorithm is used *separately* to solve for the best set of shortcuts that further improves the best layout. This is done by introducing a set of test scenarios that represent all the possible combinations of problems circumscribing the testing goal. Then, for each test Scenario E set of operation parameters are varied. Finally, various hypotheses are tested that compare the test scenarios against each other using the GLM analysis procedure with post-hoc analysis that enables the comparison of means from multiple groups while minimizing the Type I and Type II error.

5.2.1 Test Problem Description

Consider a 24 cell LLMF as shown in Figure 5.3. This LLMF tested is a simplified depiction of a 300mm wafer fabrication facility as described in Agrawal and Heragu (2006), Nazzal and El-Nashar (2007), and SEMATECH (2002).

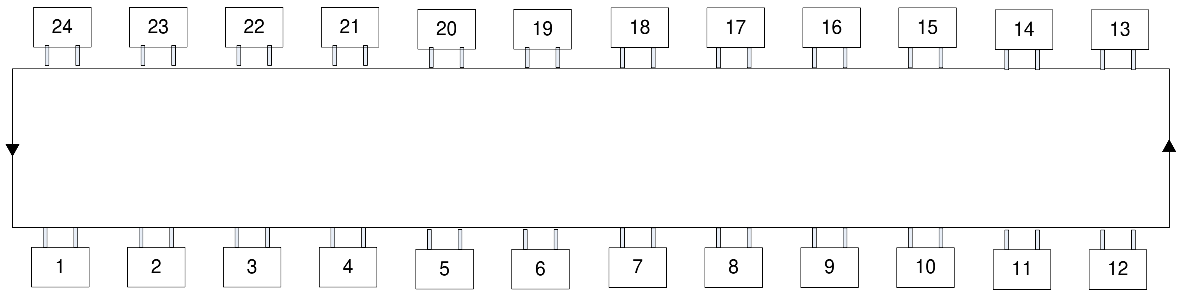

Figure 5.3: LLMF for the LLDP testing

The flow rates between the facilities are known and represented in the 'from-to' matrix; Layout X (as presented in Appendix A on page 190) is used as the base flow matrix.

5.2.2 LLDP Test Scenarios

Four scenarios are presented and described henceforth.

Table 5.8: Type of Test Scenario

	Combined	Separate
WIP	E	F
Distance	G	H

The left most column represents the design criterion used for the total cost function, while the first row represents the shortcut solution procedure. These represent the constraints of the test scenario; in essence, these constraints will affect the solution methodology as will be discussed in detail within the discussion for each test scenario.

A set of operational specific parameters are varied for each test scenario, each instance of these sets of operational specific parameters will be referred to as a test problem. Each test problem will be run 20 times (as the GA is a stochastic solution process); each run will be referred to as a test run. For each test problem, for each test scenario, each test run will first be solved. Next, given the prescribed solution, the total WIP, as prescribed by equation (52) on page 111, is then computed for each test run. In this manner, various test scenarios can be equivalently compared to each other over the same set of operational specific parameters. Hence, for each test scenario, there are three basic steps employed to determine the solution to the LLDP, as given below:

1. *Determine the Objective Function of the LLDP*
    a. Given that the total cost using the WIP is the design criteria (Test Scenario E and Test Scenario F), there are two design procedures:
        i. Combined Layout and shortcut solution procedure (Test Scenario E)
        ii. Separate Layout and shortcut solution procedure (Test Scenario F)

b. Given that the total cost using total distance travelled is the design criteria (Test Scenario G and Test Scenario H), there are two design procedures:
    i. Combined Layout and shortcut solution procedure (Test Scenario G)
    ii. Separate Layout and shortcut solution procedure (Test Scenario H)

2. *Solve the LLDP using the GA solution Procedure as prescribed by § 4*
    a. Combined Layout and shortcut solution procedure (Test Scenario E and Test Scenario G)
        i. Apply the genetic algorithm as prescribed by § 4 to solve the LLDP and get the best layout with the best set of shortcuts for the test scenario
    b. Separate Layout and shortcut solution procedure (Test Scenario F and Test Scenario H)
        i. First, solve the layout problem using the Genetic Algorithm as prescribed by § 4 (applying the modification for "layout only" problems as presented in § 4.2.3.1) to get the best layout for the test scenario

ii. Then, for the best layout use the greedy heuristic Johnson et al. (2009) to determine the best set of shortcuts (as described in § 4.2.3.2)

3. *Determine the total WIP for the best solution*

   a. For the final solution, the total WIP, as derived from equation (25) and equation (40), is then computed for each test problem

$$E(WIP_{LLMF}) = E(WIP_{CONV}) + E(WIP_{INP}) \tag{52}$$

5.2.2.1 LLDP Test Scenario E

The total cost based on the *WIP* on the LLMF is used as the design criterion while *combining* the Layout and shortcut solution procedures to solve the LLDP with shortcuts. This scenario is representative of the proposed methodology.

	Combined	Separate
WIP	E	
Distance		

The steps involved in determining the solution for a test problem for Test Scenario E is as follows:

Step 1: The objective function for the LLDP is given by equation (41).

$$Z_E = C_{WIP}\left[E\left(WIP_{INP}\right) + E\left(WIP_{CONV}\right)\right] + C_{sc} \cdot \#Shortcuts$$

Step 2: Solve the problem at hand (Layout and shortcut simultaneously) using the GA solution procedure as prescribed by § 4 to get the best layout with the best set of shortcuts for the test scenario.

Step 3: For the final solution, determine the total WIP for Test Scenario E (WIP_E) as given by equation (52).

5.2.2.2 LLDP Test Scenario F

The total cost based on the *WIP* on the LLMF is used as the design criterion to first solve for the Layout and then the greedy heuristic by Johnson et al. (2009) is used *separately* to solve for the best set of shortcuts that further improves the best layout.

	Combined	Separate
WIP		F
Distance		

The steps involved in determining the solution for a test problem for Test Scenario F is as follows:

Step 1: The objective function to determine the layout is given by

$$Z_F = C_{WIP}\left[E\left(WIP_{INP}\right) + E\left(WIP_{CONV}\right)\right] \tag{53}$$

Step 2: First, solve the problem at hand (layout problem only) using the GA solution procedure as prescribed by § 4 (see § 4.2.3.1) to get the best layout for the test scenario. Then, for the best layout use the greedy heuristic Johnson et al. (2009) to determine the best set of shortcuts as described in § 4.2.3.2.

Step 3: For the final solution, determine the total WIP for Test Scenario F (WIP_F) as given by equation (52).

5.2.2.3 LLDP Test Scenario G

The total cost based on the *total distance travelled* by the loads on the LLMF is used as the design criterion while *combining* the Layout and shortcut solution procedure to solve the LLDP with shortcuts.

	Combined	Separate
WIP		
Distance	G	

The steps involved in determining the solution for a test problem for Test Scenario G is as follows:

Step 1: The objective function for the LLDP is given by

$$Z_G = C_{Dist} \sum_{\forall i,j}^{i \neq j} \lambda_{ij} \cdot d_{ij} + C_{sc} \cdot \#Shortcuts \tag{54}$$

Where, C_{Dist} is the cost per distance unit (further discussed in § 5.2.4), d_{ij} is the distance from location i to location j, and λ_{ij} is the flow of loads from location i to location j.

Step 2: Solve the problem at hand (Layout and shortcut simultaneously) using the GA solution procedure as prescribed by § 4 to get the best layout with the best set of shortcuts for the test scenario.

Step 3: For the final solution, determine the total WIP for Test Scenario G (WIP_G) as given by equation (52).

5.2.2.4 LLDP Test Scenario H

The total cost based on the *total distance travelled* by the loads on the LLMF is used as the design criterion to first solve for the Layout and then the greedy heuristic by Johnson et al. (2009) is used *separately* to solve for the best set of shortcuts that further improves the best layout. This scenario is representative of the traditional methodology used to solve the LLDP.

	Combined	Separate
WIP		
Distance		H

The steps involved in determining the solution for a test problem for Test Scenario H is as follows:

Step 1: The objective function to determine the layout is given by

$$Z_H = C_{Dist} \sum_{\forall i,j}^{i \neq j} \lambda_{ij} \cdot d_{ij} \tag{55}$$

Where, C_{Dist} is the cost per distance unit (further discussed in § 5.2.4), d_{ij} is the distance from location i to location j, and λ_{ij} is the flow of load from location i to location j.

Step 2: First, solve the problem at hand (layout problem only) using the GA solution procedure as prescribed by § 4 (see § 4.2.3.1) to get the best layout for the test scenario. Then, for the best layout use the greedy heuristic Johnson et al. (2009) to determine the best set of shortcuts as described in § 4.2.3.2.

Step 3: For the final solution, determine the total WIP for Test Scenario H (WIP_H) as given by equation (52).

5.2.3 Parameters to be varied

The set of operational parameters in Table 5.9 are varied to generate the different test problems for each test scenario. Hence, there are 36 different test problems for each test scenario. Since the GA procedure is a stochastic solution procedure, each test problem will be solved 10 times (each referred to as a ‘test run’). Hence, there will be a total of 1440 (4 Test Scenarios * 36 Test Problems * 10 Test Runs) data points.

The number of locations in the LLMF is set to 24; Layout X is used as the base flow matrix; the speed on the conveyor is set to 3 ft/sec.

Table 5.9: Parameters to vary for LLDP

	Level			
Factor	1	2	3	4
Shortcut Cost/WIP Cost(Ω)	0.1	1	10	50
Utilization (ρ_{LCMHS})	0.15	0.5	0.85	
Turntable Turn Time	0	7	15	

Note: The speed of the conveyor is 3 ft/sec and the arrivals to the LLDP are modeled as a Markov Process

Ω is the ratio of the cost to install a shortcut to the cost of a load (one unit of WIP); Ω affects the total cost of the LLMF. It is possible to effectively and equivalently vary C_{Dist} (see § 5.2.4), and C_{sc} for all the test scenarios for all the test problems, by varying Ω and arbitrarily setting C_{WIP}.

The utilization of the conveyor is selected as a parameter to vary as it directly affects the amount of WIP in the LLMF. This has a significant effect on the choice of layout. Also, as mentioned earlier instead of varying a multitude of factors to test different scenarios, varying the utilization of the conveyor is sufficient.

The turn time of the turntable is selected as a parameter to vary as it affects the WIP level and the stability of the system. Although a particular Layout and shortcut configuration may have a significant effect on reducing the WIP in the system, it may also render the system unstable. This can be attributed to the instability introduced to the LLMF as a result of the infinite queue formation in front of an unstable turntable (i.e. the utilization of a turntable is greater than or equal to 1) blocking the output station of the preceding cell.

5.2.4 Equivalently varying the costs for all scenarios

It is important to note that a relationship has to be developed between C_{WIP} and C_{Dist} so as to properly vary both problems so the operating conditions are similar and the results to be statistically analyzed are not biased as a result of improper C_{WIP} and C_{Dist} selections. C_{WIP} is the average cost per unit of WIP, while C_{Dist} is the cost per unit distance. This section provides a detailed description on the steps involved in determining C_{Dist}.

Why is this important? For each test problem, all the scenarios should have similar likelihoods of selecting shortcuts i.e., ideally the total cost saved as a result of installing a shortcut should equivalently offset the cost of installing the shortcut. The C_{WIP} and C_{Dist} assignments will have the greatest impact on the results when $C_{SC} >> C_{WIP}$. In such cases, if C_{Dist} is too low with respect to C_{WIP}, the likelihood of selecting shortcuts is much lower for Scenario G and Scenario H than Scenario E and Scenario F. In order to balance the likelihood of selecting shortcuts across all scenarios, the objective functions from Scenario E should equal the objective functions from Scenario G. Similarly, the objective functions from Scenario F should equal the objective functions from Scenario H such that $C_{Dist} \sum_{\forall i,j}^{i \neq j} \lambda_{ij} \cdot d_{ij} = C_{WIP} \left[E\left(WIP_{INP}\right) + E\left(WIP_{CONV}\right) \right]$. Hence, setting the objective functions from Scenario E equal to Scenario G or Scenario F equal to Scenario H yields:

$$C_{Dist} = \frac{C_{WIP} \left[E\left(WIP_{INP}\right) + E\left(WIP_{CONV}\right) \right]}{\sum_{\forall i,j}^{i \neq j} \lambda_{ij} \cdot d_{ij}} \tag{56}$$

Therefore for each test problem the C_{Dist} used in Scenario G and Scenario H is determined later from the outcomes of the runs for Scenario E and Scenario F respectively.

For Scenario G, the steps involved in this determination are as follows:

Step 1: Scenario E is run 10 times.

Step 2: For each run of the test problem, at each iteration in the evaluation step of the GA as described in § 4.2.3, and for each solution visited the following data is collected: The total WIP in the LLMF and the total distance travelled by the loads for the respective solution each given by $WIP_{Total} = E\left(WIP_{INP}\right) + E\left(WIP_{CONV}\right)$ and $D = \sum_{\forall i,j}^{i \neq j} \lambda_{ij} \cdot d_{ij}$.

Step 3: For each run of the test problem, compute the average of the total WIP in the LLMF ($\overline{WIP}_{Total}$) and average total distance travelled ($\overline{D}$) for all the solutions visited.

Step 4: Using equation (56) and the outcomes from Step 3, for Scenario G of the current test problem, C_{Dist} is given by

$$C_{Dist} = C_{WIP} \cdot \sum_{\forall runs}^{A\&B} \frac{\overline{WIP}_{Total}}{\overline{D}} \tag{57}$$

Next, for the current test problem for Scenario H repeat Steps 1-4 using Scenario F as the seed to determine the cost per unit distance for Scenario H.

In this manner for each test problem, all the scenarios should have similar likelihoods of selecting shortcuts.

5.2.5 Summary of the Testing Procedure for the LLDP

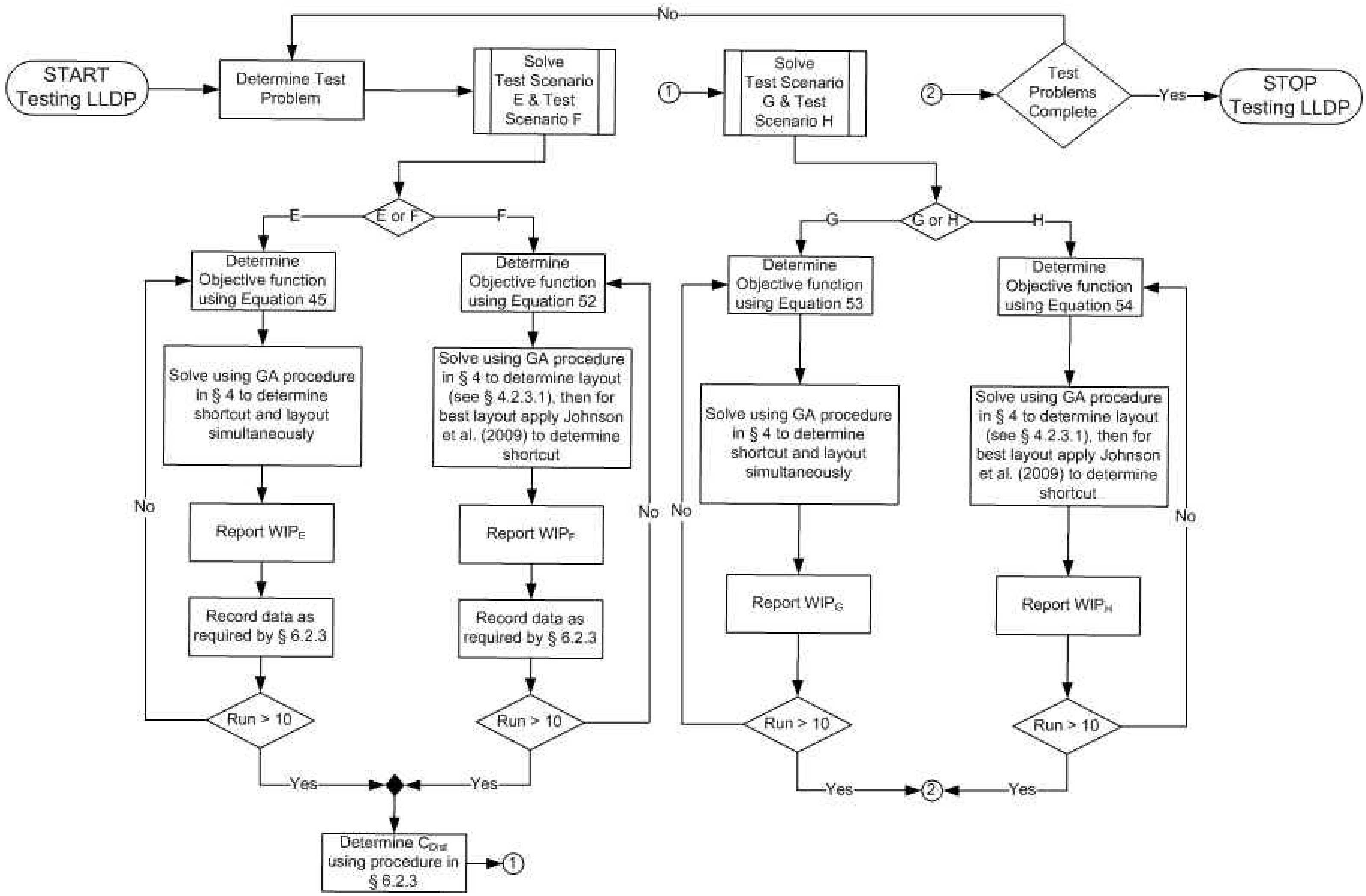

Figure 5.4: Summary of Testing Procedure for LLDP

5.2.6 Method for Analysis of Test Data for the LLDP

As presented and justified in § 5.1.4, the Generalized Linear Model (GLM) will be used to analyze the data collected from the testing of the LLDP, as GLMs enable comparing means from multiple groups to each other by incorporating post hoc analysis methods such as Tukey's Range Test (Tukey, 1977) that control for Type 1 error (McCulloch, Agarwal, & Neuhaus, 2008).

For the GLM, there are two types of input variables to be defined: the dependent variable(s), and the independent variable(s). In this case, the dependent variable is the total WIP for the LLMF as given by equation (52). The independent variables are the parameters that are varied, viz., the ratio of the cost to install a shortcut to the cost of a load (Ω), the utilization of the conveyor (ρ_{LCMHS}), and the turn time of the turntables (t). An independent variable is introduced to model the decision / optimization criterion for the layout (θ) i.e., cost based on WIP (θ = 1) *or* cost based on total distance travelled (θ = 2). Another independent variable is introduced to model the shortcut determination criterion (S) i.e., Layout and shortcuts are determined simultaneously (S = 1) or Layout and shortcuts are determined separately (S = 2). Finally, a last variable is introduced, to model the various scenarios as described in § 5.2.2, called Scenario (θS). θS represents the interaction of θ

and S, i.e. $\theta S = 1$ when $\theta = 1$ and $S = 1$ (Test Scenario E); $\theta S = 2$ when $\theta = 1$ and $\theta = 2$ (Test Scenario F); $\theta S = 3$ when $\theta = 2$ and $S = 1$ (Test Scenario G); and $\theta S = 4$ when $\theta = 2$ and $S = 2$ (Test Scenario H). This information is further summarized in Table 5.10.

Table 5.10: Description of θS

		S	
	ΘS	Combined (S = 1)	Separate (S = 2)
Θ	WIP (Θ = 1)	Scenario E (ΘS = 1)	Scenario F (ΘS = 2)
	Distance (Θ = 2)	Scenario G (ΘS = 3)	Scenario H (ΘS = 4)

Table 5.11 summarizes the independent variables (main effects) used for the GLM analysis and presents the various levels of these variables.

Table 5.11: Description of Independent Variables for GLM

	Level			
Variable	1	2	3	4
Shortcut Cost/WIP Cost (Ω)	0.1	1	10	50
Utilization (ρ_{LCMHS})	0.15	0.50	0.85	
Turntable Turn Time (t)	0	7	15	
Optimization Criteria (θ)	1	2		
Shortcut Criteria (S)	1	2		
Scenario (θS)	1	2	3	4

Here, both REGWQ and Tukey's post hoc analysis methods can test if there is a difference in the total WIP for the levels of θ, S, and θS. In this manner, the different test scenarios can be evaluated against each other, the effect of the decision criterion for the layout on the WIP can be evaluated, and the effect of the shortcut determination criterion on the WIP can be evaluated. Likewise, the effect of varying the parameters of the LLDP on the WIP can be evaluated too.

Table 5.12 presents an example of a subset of the input data for the GLM. As it can be seen, the first row of data represents the Test Scenario E (when θ = 1 and S = 1); the second row of data represents the Test Scenario F (when θ = 1 and S = 2); the third row of data represents the Test Scenario G (when θ = 2 and S = 1); and the fourth row of data represents the Test Scenario H (when θ = 2 and S = 2).

Table 5.12: Example of Subset of Input Data table for GLM

						Run				
Ω	ρ_{LCMHS}	t	θ	S	θS	1	2	…	9	10
0.1	0.15	0	1	1	1	361.6	358.6	…	357.8	359.7
1	0.5	0	1	2	2	368.5	372.9	…	365.8	367.5
10	0.85	7	2	1	3	490.7	488.6	…	487.2	483.1
50	0.85	15	2	2	4	501.6	497	…	488.2	495.7

Note: This table is presented for illustrative purposes only.

5.2.8 Hypotheses

This section describes the hypotheses that will be tested using the GLM procedure.

5.2.8.1 Hypothesis Test 1

Consider the following test scenarios:

	Combined	Separate
WIP	E	
Distance		H

This hypothesis tests if the proposed methodology (Test Scenario E) to determine the best Layout and shortcuts simultaneously has a lower total WIP than the traditional methodology (Test Scenario H) to determine the best Layout and shortcuts separately. The hypothesis is as follows:

HAD_0 There is no statistically significant difference between the total WIP of the solutions: when using the WIP as the design criterion while combining the Layout and shortcut solution procedure, *and* when using the total distance travelled as the design criterion to first solve the LLDP and then using another algorithm (for example, the greedy heuristic by Johnson et al. (2009)) to separately solve for the best set of shortcuts for the best layout. Simply stated, there is no statistically significant difference between the total WIP of the solutions as prescribed by Test Scenario E and Test Scenario H.

HAD_A The total WIP of the solution when using the WIP as the design criterion while combining the Layout and shortcut solution procedure *is less than* the total WIP of the solution when using the total distance travelled as the design criterion to first solve the LLDP and then using another algorithm (for example, the greedy heuristic by Johnson et al. (2009)) to separately solve for the best set of shortcuts for the best layout. Simply stated, the total WIP of the solution as prescribed by Test Scenario E is less *than* the total WIP of the solution as prescribed by Test Scenario H.

5.2.8.2 Hypothesis Test 2

Consider the following test scenarios:

	Combined	Separate
WIP	E	F
Distance		

This hypothesis tests if the combined method for determining the Layout and shortcuts simultaneously (Test Scenario E) has a lower total WIP than the separate method for determining the Layout and shortcuts (Test Scenario F), while using the cost based on the WIP as the design criterion. The hypothesis is as follows:

HAB_0 There is no statistically significant difference between the total WIP of the solutions: when using the WIP as the design criterion while combining the Layout and shortcut solution procedure, *and* when using the WIP as the design criterion to first solve the LLDP and then using another algorithm (for example, the greedy heuristic by (A Johnson et al., 2009)) to separately solve for the best set of shortcuts for the best layout. Simply stated, there is no statistically significant difference between the total WIP of the solutions as prescribed by Test Scenario E and Test Scenario F.

HAB_A The total WIP of the solution when using the WIP as the design criterion while combining the Layout and shortcut solution procedure *is less than* the total WIP of the solution when using the WIP as the design criterion to first solve the LLDP and (for example, the greedy heuristic by Johnson et al. (2009)) to separately solve for the best set of shortcuts for the best layout. Simply stated, the total WIP of the solution as prescribed by Test

Scenario E *is less than* the total WIP of the solution as prescribed by Test Scenario F.

5.2.8.3 Hypothesis Test 3

Consider the following test scenarios:

	Combined	Separate
WIP	E	
Distance	G	

This hypothesis tests if the combined method for determining the Layout and shortcuts simultaneously while using the WIP as the design criterion (Test Scenario E) has a lower total WIP than the combined method for determining the Layout and shortcuts simultaneously while using the total distance travelled as the design criterion (Test Scenario G). The hypothesis is as follows:

HAC_0 There is no statistically significant difference between the total WIP of the solutions: when using the WIP *or* when using the total distance travelled as the design criterion as the design criterion while combining the Layout and shortcut solution procedure. Simply stated, there is no statistically significant difference between the total WIP of the solutions as prescribed by Test Scenario E and Test Scenario G.

HAC_A The total WIP of the solution when using the WIP as the design criterion while combining the Layout and shortcut solution procedure *is less than* the total WIP of the solution when using the total distance travelled as the design criterion while combining the Layout and shortcut solution procedure. Simply stated, the total WIP of the solution as prescribed by Test Scenario E *is less than* the total WIP of the solution as prescribed by Test Scenario G.

5.2.8.4 Hypothesis Test 4

Consider the following test scenarios:

	Combined	Separate
WIP		
Distance	G	H

This hypothesis tests if the combined method for determining the Layout and shortcuts simultaneously (Test Scenario G) has a lower total WIP than the separate method for determining the Layout and shortcuts (Test Scenario H), while using the cost based on the total distance travelled as the design criterion. The hypothesis is as follows:

HCD_0 There is no statistically significant difference between the total WIP of the solutions: when using the total distance travelled as the design criterion while combining the Layout and shortcut solution procedure, *and* when using the total distance travelled as the design criterion to first solve the LLDP and then using another algorithm (for example, the greedy heuristic by Johnson et al. (2009)) to separately solve for the best set of shortcuts for the best layout. Simply stated, there is no statistically significant difference between the total WIP of the solutions as prescribed by Test Scenario G and Test Scenario H.

HCD_A The total WIP of the solution when using the WIP as the design criterion while combining the Layout and shortcut solution procedure *is less than* the total WIP of the solution when using the WIP as the design criterion to first solve the LLDP and then using another algorithm separately to solve for the set of shortcuts. Simply stated, the total WIP of the solution as prescribed by Test Scenario G *is less than* the total WIP of the solution as prescribed by Test Scenario H.

5.2.8.5 Hypothesis Test 5

Consider the following test scenarios:

	Combined	Separate
WIP		F
Distance		H

This hypothesis is to test if the separate method for prescribing the shortcuts while using the WIP as the design criterion has a lower total WIP than the separate method for prescribing the shortcuts while using the total distance travelled as the design criterion. The hypothesis is as follows:

HBD_0 There is no statistically significant difference between the total WIP of the solutions: when using the WIP or when using the total distance travelled as the design criterion to first solve the LLDP and then using another algorithm (for example, the greedy heuristic by Johnson et al. (2009)) to separately solve for the best set of shortcuts for the best layout. Simply stated, there is no statistically significant difference between the total WIP of the solutions as prescribed by Test Scenario F and Test Scenario H.

HBD_A The total WIP of the solution when using the WIP as the design criterion while combining the Layout and shortcut solution procedure *is less than* the total WIP of the solution as prescribed by using the total distance travelled as the design criterion while combining the Layout and shortcut solution procedure. Simply stated, the total WIP of the solution as prescribed by Test Scenario F *is less than* the total WIP of the solution as prescribed by Test Scenario H.

5.2.9 Fine Tuning the Genetic Algorithm Solution Procedure

The test problem as discussed in § 5.2.1 on page 107 will be solved using a genetic algorithm. There have been numerous studies on the best settings for a GA under various conditions. These conditional settings have been discussed in great detail in § 4.2.1.1 on page 80. Table 5.13 presents the parameters of the GA that can be varied to fine tune the solution algorithm.

Table 5.13: Parameters to vary to fine-tune Solution Algorithm

	Level		
Parameter	1	2	3
Elitism	Yes	No	
Selection Type	Ranked	Tournament	
Selection Rate	0.25	0.75	Uniform U(0.24, 0.76)
Crossover Rate	0.4	0.6	0.8
Mutation Rate	0.01	0.03	Uniform U(0.01, 0.05)
Population Size	30	50	100
Maximum Iterations	1000	3000	5000
Termination Condition	100	500	1000

The elitism parameter is chosen as suggested by various literature to improve the chances of finding the best solution quickly (Cheng et al., 1996; Deb, Pratap, Agarwal, & Meyarivan, 2002; Deb & Goel, 2001; Greenhalgh & Marshall, 2000; Haupt & Haupt, 2004). Rudolph (2002) suggests that varying (iteratively or over time) both the selection and mutation rates while implementing elitism improves the chances of finding the globally optimal solution. After rigorous testing, Haupt & Haupt (2004) too suggest that varying the selection and mutation rate has a greater effect on the solution than varying the crossover rate. Hence, the selection rate is varied iteratively and uniformly between 0.50 and 0.75, while the mutation rate is varied iteratively and uniformly between 0.01 and 0.05. De Jong (1975) suggests using a crossover rate of 0.6; hence, the crossover rate is set to 0.6.

The literature suggests using a variety of population sizes; small population sizes ($p \leq 30$) improve the short term performance of the GA, while large population sizes ($p > 30$) improve the long run performance of the GA. There is a tradeoff between the population sizes that can be determined for the problem at hand. With small population sizes the GA converges quickly but could get stuck in a local optima (since fewer solutions are visited) while large population sizes are computationally expensive. Hence testing will be performed to determine the best population size to use among the listed population sizes (30, 50, 100).

5.2.9.1 Outcomes of Parameter Sweep for the GA solution Algorithm

The parameters in Table 5.12 were varied over an initial set of problems. Table 5.14 presents the set of parameters that had the best performance in terms of: computational time and quality of solution (lowest WIP).

Table 5.14: Final Parameters for GA solution Algorithm

Parameter	Level
Elitism	Yes
Selection Type	Tournament
Selection Rate	Uniform U(0.24, 0.76)
Crossover Rate	0.6
Mutation Rate	0.03
Population Size	30
Maximum Iterations	5000
Termination Condition	500

6 ANALYSIS OF RESULTS

This chapter present the results and their interpretations for the testing procedures presented § 5.1 and § 0. The discussion of the outcomes are provided in § 7 from page 173. All the analysis was performed in SAS 9.2 using the GLM procedure. All of the tests are performed at the 95% confidence level.

6.1 Results for the Expected Value of WIP at the Input Station testing

This section presents the results and their interpretations for the testing procedure presented in § 5.1, i.e., testing the analytical estimate for the total WIP at the Input Stations of a conveyor.

It should be noted that the test values for $\rho_{LCMHS} = 0.9$ were omitted from the GLM analysis. For $\rho_{LCMHS} = 0.9$, the analytical model does not provide accurate estimates of the total WIP at the input stations. This is not surprising since many of the analytical estimates for queueing models are known to be less accurate at higher levels of utilization requiring alternative formulations at those levels (Buzacott & Shanthikumar, 1993; Hopp & Spearman, 2000). It was intended that the proposed analytical estimate would adequately model the total WIP at the input stations for all levels of utilization; but the inability to capture the dynamics of the system at utilization levels higher that 0.9 warrants further investigation and is included as one of the items on the list of future work. This section presents all the results (even those for the utilization level 0.9) to further validate the exclusion of test values from the GLM analysis.

For each layout, the total WIP at the input stations from the testing (simulation model and analytical estimate) is presented in Appendix C on page 194. For each layout the absolute relative error between the simulation model and the analytical estimate is computed for each replication and listed in Appendix D on page 198. The absolute relative error is given by

$$\text{Absolute Relative Error} = \frac{\left| WIP_{Simulation} - WIP_{Analytical} \right|}{WIP_{Simulation}} \qquad (58)$$

Using the data from Appendix C, summary statistics on the efficacy of the analytical estimate are presented. In Table 6.1, the absolute relative errors {using equation (58)} are presented. The first row represents the absolute relative errors in the analytical estimate for each layout for all the levels of utilization. Each subsequent row presents the absolute relative errors in the analytical estimate for each Layout at the specified level of utilization.

The overall performance of the analytical estimate for the total WIP at the input stations of a conveyor is well within the acceptable range of error as presented in past studies (Atmaca, 1994; Y Bozer & Hsieh, 2004, 2005; Hsieh & Bozer, 2005; Nazzal et al., 2010, 2008) Furthermore, the analytical model's accuracy is higher at lower utilization levels of the conveyor.

Table 6.1: Average Absolute relative error for each Layout at different levels of ρ_{LCMHS}

	Absolute relative error		
ρ_{LCMHS}	Layout X	Layout Y	Layout Z
All	9.54%	10.06%	7.71%
0.15	1.51%	1.17%	7.90%
0.3	5.07%	4.33%	5.14%
0.45	4.37%	4.63%	1.90%
0.6	6.45%	7.11%	4.12%
0.75	11.59%	12.55%	6.03%
0.9	28.28%	30.56%	21.20%

Table 6.2 provides another perspective of the absolute relative errors of the results for each Layout based on levels of c_a^2. Again, the overall performance of the analytical estimate for the total WIP at the input stations of a conveyor for different levels of c_a^2 is well within the acceptable range of error. Also, when $\rho_{LCMHS} = 0.9$ is excluded from the calculations the performance of the analytical estimate is very good and excels at $c_a^2 = 1$, i.e., Markovian arrival process.

Table 6.2: Average Absolute relative error for each layout at different levels of c_a^2

	Average Absolute relative error for					
	Layout X		Layout Y		Layout Z	
c_a^2	All	ρ < 0.9	All	ρ < 0.9	All	ρ < 0.9
0.5	10.44%	10.07%	8.89%	9.83%	7.57%	6.81%
0.77	6.65%	5.18%	6.99%	4.35%	5.98%	5.61%
1	7.00%	2.65%	7.68%	2.45%	7.29%	4.65%
1.23	9.70%	3.84%	11.51%	5.12%	7.94%	3.78%
1.5	13.94%	7.25%	15.21%	8.03%	9.80%	4.24%

Next, the average errors for each layout at different levels of conveyor utilization and arrival variability are presented in Appendix E on page 202.

Figure 6.1, Figure 6.2, and Figure 6.3 illustrate the average error for each Layout at each level of c_a^2. Notably, when $c_a^2 \leq 1$ the analytical estimate is consistently less than the simulation estimate while the converse is true when $c_a^2 > 1$. Clearly, the analytical estimate does not perform well when $\rho_{LCMHS} = 0.9$. Conversely, the analytical estimate performs better at lower conveyor utilizations.

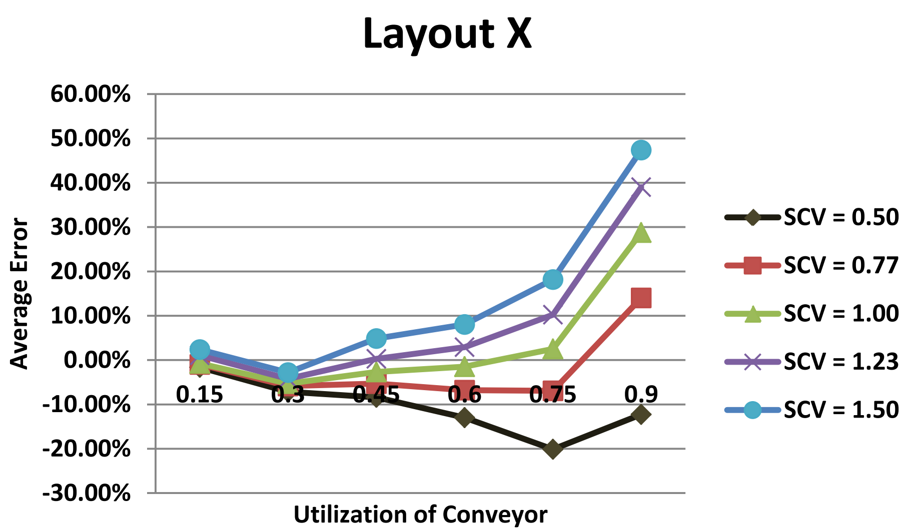

Figure 6.1: Average Error for Layout X

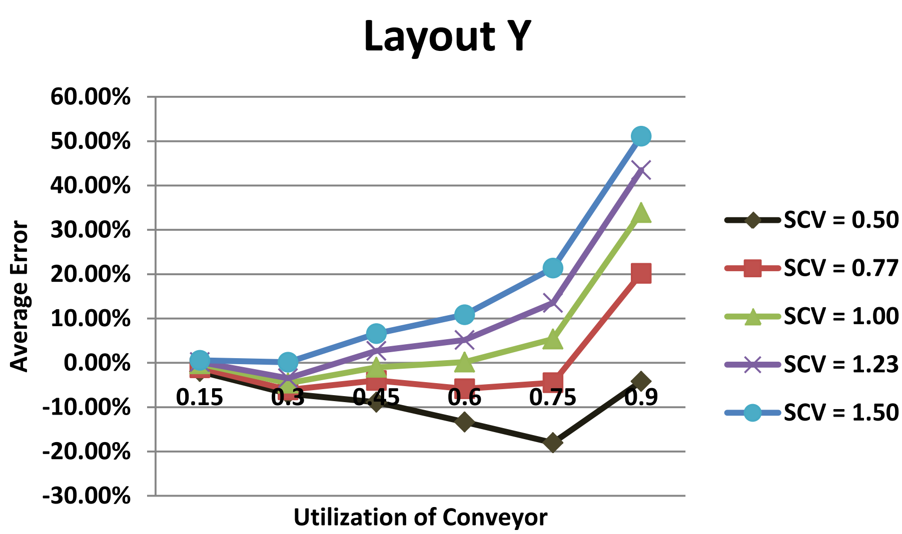

Figure 6.2: Average Error for Layout Y

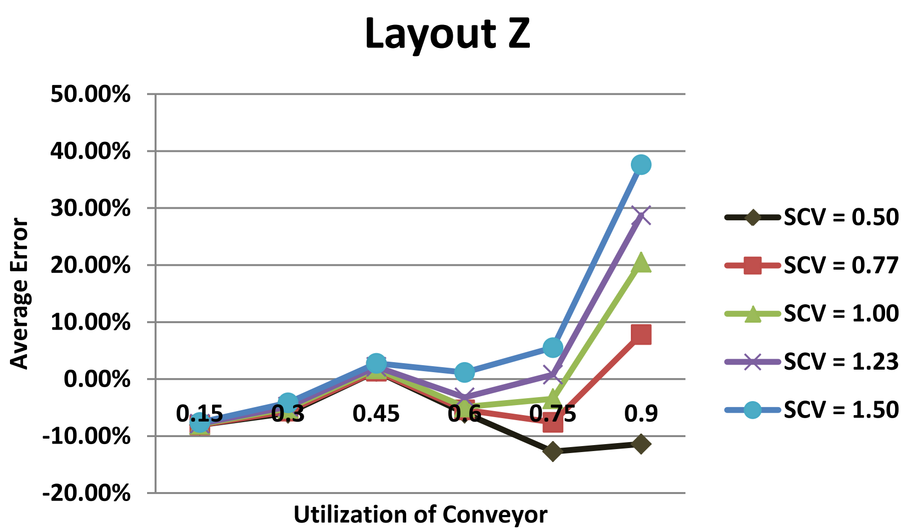

Figure 6.3: Average Error for Layout Z

Given the high level overview of the results, further probing of the data is warranted. The GLM analysis performed in the next section probes the results and provides statistical validation of some of the observances made in the high level overview while simultaneously determining relationships among various parameters and their overall effect on the total WIP at the input stations of the conveyor. The details of the design of the GLM analysis have been provided in § 5.1.4 on page 97.

6.2 GLM Analysis for the Expected Value of WIP at the Input Station

It is important to note that for each layout (X, Y, and Z) a separate GLM analysis is performed. For each layout, only the highlights of the GLM analysis are presented in this section.

For Layout X, the exact output of the GLM analysis procedure from SAS is presented in Appendix F on page 203. For Layout Y, the exact output of the GLM analysis procedure from SAS is presented in Appendix G on page 213. For Layout Z, the exact output of the GLM analysis procedure from SAS is presented in Appendix H on page 222.

6.2.1 Analysis of Variance

The following description is adapted from SAS Institute Inc (2010). In the analysis of variance (ANOVA), a *dependent variable,* i.e. WIP (total WIP at the input stations), is measured under experimental conditions identified by classification variables, known as *independent variables*, as described in Table 5.6 on page 101.

6.2.1.1 ANOVA for Layout X

Table 6.3 presents the analysis of variance of the total WIP at the input stations.

Table 6.3: ANOVA of the WIP at the Input Stations for Layout X

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	12761.02	750.648	2931	<.0001
Error	482	123.4226	0.25606		
Corrected Total	499	12884.44			

R-Square	Coeff Var	Root MSE	WIP Mean
0.9902	12.56	0.509938	4.059303

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Utilization (ρ_{LCMHS})	4	12708.34	3177.086	12407	<.0001
SCV (c_a^2)	4	24.7323	6.18308	24.15	<.0001
M	1	0.25341	0.25341	0.99	0.32
SCVM	4	24.7323	6.18308	24.15	<.0001
RHOM	4	2.95521	0.7388	2.89	0.022

To summarize:

- The overall fit of the model is significant and accounts for 99.02% of the error. Hence, the comparison of means based on this model as presented henceforth is considered reliable.

6.2.1.2 ANOVA for Layout Y

Table 6.4 presents the analysis of variance of the total WIP at the input stations.

Table 6.4: ANOVA of the WIP at the Input Stations for Layout Y

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	13732.3	807.7824	2550	<.0001
Error	482	152.7002	0.31681		
Corrected Total	499	13885			

R-Square	Coeff Var	Root MSE	WIP Mean
0.989	13.38	0.562855	4.20814

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Utilization (ρ_{LCMHS})	4	13652.73	3413.181	10774	<.0001
SCV (c_a^2)	4	31.85144	7.96286	25.13	<.0001
M	1	2.95744	2.95744	9.34	0.002
SCVM	4	31.85144	7.96286	25.13	<.0001
RHOM	4	12.91498	3.22874	10.19	<.0001

To summarize:

- The overall fit of the model is significant and accounts for 98.9% of the error. Hence, the comparison of means based on this model as presented henceforth is considered to be reliable.

6.2.1.3 ANOVA for Layout Z

Table 6.5 presents the analysis of variance of the total WIP at the input stations.

Table 6.5: ANOVA of the WIP at the Input Stations for Layout Z

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	14966.52	880.3834	13712	<.0001
Error	482	30.94774	0.06421		
Corrected Total	499	14997.47			

R-Square	Coeff Var	Root MSE	WIP Mean
0.998	6.094	0.26801	4.398252

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Utilization (ρ_{LCMHS})	4	14950.22	3737.554	58211	<.0001
SCV (c_a^2)	4	5.20085	1.30021	20.25	<.0001
M	1	1.9404	1.9404	30.22	<.0001
SCVM	4	5.20085	1.30021	20.25	<.0001
RHOM	4	3.96128	0.99032	15.42	<.0001

To summarize:

- The overall fit of the model is significant and accounts for 99.8% of the error. Hence, the comparison of means based on this model as presented henceforth is considered to be reliable.

6.2.2 Comparison of Means

Here, for each of the independent variables (main effects) used for each level of the main effect, the means of the dependent variable (WIP) can be compared using REGWQ and Tukeys multiple comparison test (SAS Institute Inc, 2010). In other words, for each main effect the comparison of means test elucidates any difference in the means of the dependent variable for each level of the main effect, thereby clarifying the influence (or lack thereof) of the main effects on the dependent variable; while controlling for Type I and Type II errors.

6.2.2.1 Variable: Utilization of Conveyor (ρ_{LCMHS})

In the tables, the dependent variable WIP is compared across the different levels of the main effect ρ_{LCMHS} using REGWQ and Tukeys multiple comparison tests for each layout. It should be noted that means with the same letter (under the grouping columns) are not significantly different. This test is performed to ensure the tested system is performing as expected; it serves to validate the tested system.

Table 6.6: REGWQ and Tukeys multiple comparison test for ρ_{LCMHS} for Layout X

			Grouping*	
ρ_{LCMHS}	N	Mean WIP	REGWQ	Tukey
0.75	100	13.67	A	A
0.6	100	4.45	B	B
0.45	100	1.59	C	C
0.3	100	0.49	D	D
0.15	100	0.10	E	E

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.7: REGWQ and Tukeys multiple comparison test for ρ_{LCMHS} for Layout Y

			Grouping*	
ρ_{LCMHS}	N	Mean WIP	REGWQ	Tukey
0.75	100	13.67	A	A
0.6	100	4.45	B	B
0.45	100	1.59	C	C
0.3	100	0.49	D	D
0.15	100	0.10	E	E

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.8: REGWQ and Tukeys multiple comparison test for ρ_{LCMHS} for Layout Z

			Grouping*	
ρ_{LCMHS}	N	Mean WIP	REGWQ	Tukey
0.75	100	13.67	A	A
0.6	100	4.45	B	B
0.45	100	1.59	C	C
0.3	100	0.49	D	D
0.15	100	0.10	E	E

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

To summarize:

- For each layout, at each level of ρ_{LCMHS} there is a significant difference in the total WIP at the input stations
- For each layout, as ρ_{LCMHS} increases the total WIP at the input stations increase

6.2.2.2 Variable: Squared Coefficient of variation of Arrivals (c_a^2)

In the tables, the dependent variable WIP is compared across the different levels of the main effect c_a^2 using REGWQ and Tukeys multiple comparison tests for each layout. It should be noted that means with the same letter (under the grouping columns) are not significantly different. This test is performed to ensure the system tested is performing as expected; it serves to validate the system tested.

Table 6.9: REGWQ and Tukeys multiple comparison test for c_a^2 for Layout X

			Grouping*			
c_a^2	N	Mean WIP	REGWQ		Tukey	
1.5	100	4.38	A		A	
1.23	100	4.20		B	A	B
1	100	4.06	C	B	C	B
0.77	100	3.91	C	D	C	D
0.5	100	3.74		D		D

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.10: REGWQ and Tukeys multiple comparison test for c_a^2 for Layout Y

			Grouping*			
c_a^2	N	Mean WIP	REGWQ		Tukey	
1.5	100	4.57	A		A	
1.23	100	4.37		B	A	B
1	100	4.21	C	B	C	B
0.77	100	4.04	C	D	C	D
0.5	100	3.85		D		D

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.11: REGWQ and Tukeys multiple comparison test for c_a^2 for Layout Z

			Grouping*			
c_a^2	N	Mean WIP	REGWQ		Tukey	
1.5	100	4.56	A		A	
1.23	100	4.46		B	A	B
1	100	4.39	C	B	C	B
0.77	100	4.33	C	D	C	D
0.5	100	4.26		D		D

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

To summarize:

- For each layout, for adjacent levels of c_a^2 there is no significant difference in the total WIP at the input stations
- For each layout, for non-adjacent levels of c_a^2 there is a significant difference in the total WIP at the input stations
- For each layout, as c_a^2 increases the total WIP at the input stations increase

6.2.2.3 Variable: WIP Data Source – Simulation or Analytical Estimate (M)

In the tables, the dependent variable WIP is compared across the different levels of the main effect 'M' using REGWQ and Tukeys multiple comparison tests for each layout. It should be noted that means with the same letter (under the grouping columns) are not significantly different. The main effect 'M' is introduced to test if there is a significant difference between the simulation output (M = 1) and the analytical estimate (M = 0).

Table 6.12: REGWQ and Tukeys multiple comparison test for M for Layout X

			Grouping*	
M	N	Mean WIP	REGWQ	Tukey
1	250	4.08	A	A
0	250	4.04	A	A

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.13: REGWQ and Tukeys multiple comparison test for M for Layout Y

			Grouping*	
M	N	Mean WIP	REGWQ	Tukey
1	250	4.29	A	A
0	250	4.13	B	B

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.14: REGWQ and Tukeys multiple comparison test for M for Layout Z

			Grouping*	
M	N	Mean WIP	REGWQ	Tukey
1	250	4.46	A	A
0	250	4.34	B	B

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

To summarize:

- For Layout X, there is no significant difference between the analytical estimate and the simulation estimate of the mean total WIP at the input stations
- For Layout Y and Layout Z, there is significant difference between the analytical estimate and the simulation estimate of the mean total WIP at the input stations
- For each layout, the total WIP estimate at the input stations from simulation (M = 1) is higher than the total WIP estimate at the input stations from the analytical estimate (M = 0)

6.2.2.4 Variable: Interaction between M and c_a^2 (SCVM)

In the tables, the dependent variable WIP is compared across the different levels of the main effect 'SCVM' using REGWQ and Tukeys multiple comparison tests for each layout. It should be noted that means with the same letter (under the grouping columns) are not significantly different. It is introduced to test if there is a significant difference between the simulation output (M = 1) and the analytical estimate (M = 0) at different levels of c_a^2.

Table 6.15: REGWQ and Tukeys multiple comparison test for SCVM for Layout X

			Grouping*		
SCVM	N	Mean WIP	REGWQ	Tukey	
9	50	4.73	A	A	
7	50	4.37	B		B
5	50	4.08	C	C	B
2	50	4.04	C	C	
4	50	4.04	C	C	
6	50	4.04	C	C	
8	50	4.04	C	C	
10	50	4.04	C	C	
3	50	3.78	C	C	
1	50	3.45	D		D

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.16: REGWQ and Tukeys multiple comparison test for SCVM for Layout Y

			Grouping*			
SCVM	N	Mean WIP	REGWQ		Tukey	
9	50	5.02	A		A	
7	50	4.62	B			B
5	50	4.28	C		C	B
2	50	4.13	C		C	
4	50	4.13	C		C	
6	50	4.13	C		C	
8	50	4.13	C		C	
10	50	4.13	C		C	
3	50	3.94	C		C	
1	50	3.57	D			D

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.17: REGWQ and Tukeys multiple comparison test for SCVM for Layout Z

			Grouping*			
SCVM	N	Mean WIP	REGWQ		Tukey	
9	50	4.65	A		A	
2	50	4.46		B		B
4	50	4.46		B		B
6	50	4.46		B		B
8	50	4.46		B		B
10	50	4.46		B		B
7	50	4.45		B		B
5	50	4.31	C	B	C	B
3	50	4.20	C	D	C	D
1	50	4.06		D		D

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

To summarize:

- For Layout X and Layout Y, there is no significant difference in the total WIP at the input stations from the analytical estimate and from the simulation model when c_a^2 is 0.77 and 1
- For Layout Z, there is no significant difference in the total WIP at the input stations from the analytical estimate and from the simulation model when c_a^2 is 1 and 1.23

6.2.2.5 Variable: Interaction between M and ρ_{LCMHS} (RHOM)

In the tables, the dependent variable WIP is compared across the different levels of the main effect 'RHOM' using REGWQ and Tukeys multiple comparison tests for each layout. It should be noted that means with the same letter (under the grouping columns) are not significantly different. It is introduced to test if there is a significant difference between the simulation output (M = 1) and the analytical estimate (M = 0) at different levels of conveyor utilization (ρ_{LCMHS}).

Table 6.18: REGWQ and Tukeys multiple comparison test for RHOM for Layout X

			Grouping*	
RHOM	N	Mean WIP	REGWQ	Tukey
9	50	13.85	A	A
10	50	13.50	B	B
8	50	4.48	C	C
7	50	4.41	C	C
6	50	1.60	D	D
5	50	1.57	D	D
4	50	0.51	E	E
3	50	0.48	E	E
1	50	0.10	F	F
2	50	0.10	F	F

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.19: REGWQ and Tukeys multiple comparison test for RHOM for Layout Y

			Grouping*	
RHOM	N	Mean WIP	REGWQ	Tukey
9	50	14.57	A	A
10	50	13.77	B	B
8	50	4.61	C	C
7	50	4.60	C	C
6	50	1.65	D	D
5	50	1.64	D	D
4	50	0.52	E	E
3	50	0.50	E	E
1	50	0.10	F	F
2	50	0.10	F	F

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

Table 6.20: REGWQ and Tukeys multiple comparison test for RHOM for Layout Z

			Grouping*	
RHOM	N	Mean WIP	REGWQ	Tukey
9	50	15.06	A	A
10	50	14.60	B	B
8	50	4.87	C	C
7	50	4.70	D	D
6	50	1.76	E	E
5	50	1.72	E	E
4	50	0.54	F	F
3	50	0.52	F	F
1	50	0.10	G	G
2	50	0.10	G	G

Note: These tests control the Type I experimentwise error rate
* Means with the same letter are not significantly different

To summarize:

- For Layout X and Layout Y, there is no significant difference in the total WIP at the input stations from the analytical estimate and simulation model when ρ_{LCMHS} is 0.15, 0.3, 0.45, and 0.6
- For Layout Z, there is no significant difference in the total WIP at the input stations from the analytical estimate and simulation model when ρ_{LCMHS} is 0.15, 0.3, and 0.45

6.2.3 Evaluation of Hypotheses

Consider the main effect ‘M’, which is an indicator variable specifying where the output is from the simulation model (M = 1) of from the analytical model (M = 0). The results from the GLM analysis as presented in § 6.2.2.3, indicate that the analytical estimate and the simulation model are significantly different from each other when compared over all levels of utilization and arrival process variability (c_a^2). Hence, from a statistical perspective the analytical estimate for the total WIP cannot be considered a general methodology that holds true over all levels of utilization and c_a^2. With this in mind, one could make the statement with respect to hypothesis test 1 as presented in § 5.1.5.1:

- $H1_0$ (Null hypothesis for Hypothesis Test 1) *is rejected*

However, from a practical perspective, the results as presented in Table 6.1 show that the average absolute relative error of the proposed analytical estimate while excluding conveyor utilization greater than or equal to 0.75 is 4.47%. This error is well within the acceptable range of error as presented in past studies (Atmaca, 1994; Y Bozer & Hsieh, 2004, 2005; Hsieh & Bozer, 2005; Nazzal et al., 2010, 2008)

Consider the interaction between the level of utilization and M, i.e., the main effect 'RHOM'. The results from the GLM analysis, as presented in § 6.2.2.5, indicate that the analytical estimate and the simulation model are not significantly different from each other when the conveyor utilization is less than 0.5.

Hence, one could make the statements with respect to hypothesis test 2 as presented in § 5.1.5.2 as follows:

- Given that the utilization of the conveyor is less than 0.5; $H2_0$ (Null hypothesis for Hypothesis Test 2) *is not rejected*
- Given that the utilization of the conveyor is greater than 0.5; $H2_0$ (Null hypothesis for Hypothesis Test 2) *is rejected*

Consider the interaction between c_a^2 and M, i.e., the main effect 'SCVM'. The results from the GLM analysis, as presented in § 6.2.2.4, indicate that the analytical estimate and the simulation model are not significantly different from each other when c_a^2 is 1.

Hence, one could make the statements:

- Given that the utilization of the conveyor is less than 0.9; $H3_0$ (Null hypothesis for Hypothesis Test 3 as presented in § 5.1.5.3) *is rejected*
- Given that the utilization of the conveyor is less than 0.9; $H4_0$ (Null hypothesis for Hypothesis Test 4 as presented in § 5.1.5.4) *is not rejected*
- Given that the utilization of the conveyor is less than 0.9; $H5_0$ (Null hypothesis for Hypothesis Test 5 as presented in § 5.1.5.5) *is rejected*

6.3 Results for the Looped Layout Design Problem testing

This section presents the results and their interpretations for the testing procedure as presented § 0, i.e., testing the efficacy of the proposed methodology to determine the layout of a LLMF with an LCMHS that has shortcuts such that it has the least WIP amongst the alternative (traditional) methods used to determine the layout of a LLMF.

The resultant WIP for the best solutions for each replication of each test problem from the testing is presented in Appendix I on page 231. For the best solutions from the testing, the resulting number of shortcuts is presented in Appendix J on page 237, the resulting number of iterations needed to find the best solutions is presented in Appendix K on page 243, and the resulting time (in minutes) needed to find the best solutions is presented in Appendix L on page 249. The entire list of each solution (machine and shortcut assignment) will be available upon request[2]. The proceeding tables present a high level of summary analysis of the data from multiple perspectives.

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[2] This list has been excluded from the document as it does not add any value but takes up over a 100 pages. Upon request, the author will provide the solution list.

Table 6.21 presents a summary of the results from the perspective of the type of scenario. Notably, Scenario E has the lowest WIP. It is also interesting to note that Scenarios A and C (combined shortcut methodology) require fewer iterations to reach the best solution but take longer to solve as a result of the additional computation per iteration (to determine the shortcuts). Lastly, the choice of scenario does not seem to have an effect on the number of shortcuts for the best solutions.

Table 6.21: LLDP Results Summary with regards to Scenario

	Average			
Scenario	WIP	# Shortcuts	# Iterations	Time (min)
E	151.50	12.31	1164.34	72.35
F	293.12	12.18	1419.97	43.57
G	165.68	10.94	1182.63	72.70
H	293.57	11.57	1384.09	39.52

Table 6.22 presents a summary of the results from the perspective of the utilization of the conveyor (ρ_{LCMHS}). As expected, when the utilization of the conveyor increases, the WIP increases. It is interesting to note that as ρ_{LCMHS} increases, the number of shortcuts in the LLMF increases. However, ρ_{LCMHS} does not seem to have an effect on the number of iterations and the time required to reach the best solution.

Table 6.23 presents a summary of the results from the perspective of the turntime of the turntables. Contrary to expectations, the turntime does not seem to have an effect on the WIP in the LLMF, the number of shortcuts, the number of iterations, or the time required to reach the best solution.

Table 6.22: LLDP Results Summary with regards to ρ_{LCMHS}

	Average			
ρ_{LCMHS}	WIP	# Shortcuts	# Iteration	Time (min)
0.15	74.66	9.59	1277.41	56.75
0.5	230.41	12.11	1296.23	60.25
0.85	372.84	13.54	1289.62	54.11

Table 6.23: LLDP Results Summary with regards to t

	Average			
t	WIP	# Shortcuts	# Iteration	Time (min)
0	222.27	11.74	1286.98	56.98
7	225.73	11.71	1297.76	57.57
15	229.92	11.79	1278.53	56.56

Table 6.24 presents a summary of the results from the perspective of the ratio between the cost to install a shortcut and the cost of s single load (Ω). As expected, when Ω increases the WIP increases and the number of shortcuts decreases. Ω does not seem to have an effect on the number of iterations or the time required to reach the best solution.

Table 6.24: LLDP Results Summary with regards to Ω

	Average			
Ω	WIP	# Shortcuts	# Iteration	Time (min)
0.1	203.02	21.10	1238.19	54.47
1	204.93	16.70	1273.45	55.49
10	228.88	6.45	1283.09	54.64
50	267.05	2.74	1356.29	63.53

Table 6.25 presents a summary of the results from the perspective of the optimization criteria (θ). It seems that minimizing the WIP (θ = 1), as opposed to minimizing the total distance travelled (θ = 2) yields LLMFs with lower WIP and more shortcuts. θ does not seem to have an effect on the number of iterations or the time required to reach the best solution.

Table 6.25: LLDP Results Summary with regards to θ

	Average			
θ	WIP	# Shortcuts	# Iteration	Time (min)
1	222.31	12.24	1292.15	57.96
2	229.63	11.25	1283.36	56.11

Table 6.26 presents a summary of the results from the perspective of the shortcut criteria (S). It seems that Using the combined method to determine the shortcuts (S = 1), as opposed to separate method to determine the shortcuts (S = 2), yields LLMFs with lower WIP. Also, as noticed earlier the combined shortcut methodology requires fewer iterations to reach the best solution but takes longer to solve as a result of the additional computa-

tions per iteration (to determine the shortcuts). *S* does not seem to have an effect on the number of shortcuts for the best solutions.

Table 6.26: LLDP Results Summary with regards to *S*

	Average			
S	WIP	# Shortcuts	# Iteration	Time (min)
1	158.59	11.62	1173.48	72.53
2	293.35	11.87	1402.03	41.55

Given the high level overview of the results further probing of the data is warranted. The GLM analysis performed in the next section probes the results and provides statistical validation of some of the observances made in the high level overview while simultaneously determining relationships among various parameters and their overall effect on the total WIP in the LLMF. The details of the design of the GLM analysis have been provided in § 5.2.6 on page 122.

6.4 GLM Analysis for the Looped Layout Design Problem

In this case the *dependent variable,* i.e. WIP is determined for each test problem using equation (52) on page 111 while the *independent variables* are as described in Table 5.11 on page 123. The exact output of the GLM procedure from SAS is presented in

Appendix M on page 255; however, the highlights of the results are presented in this section.

6.4.1 Analysis of Variance (ANOVA)

Table 6.27 presents the analysis of variance of the WIP for the LLDP test problem. The following description is adapted from SAS Institute Inc (2010). In the analysis of variance (ANOVA), a *dependent variable,* i.e. WIP, is measured under experimental conditions identified by classification variables, known as *independent variables*.

Table 6.27: ANOVA of the WIP for the LLDP

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	28919642	2891964	944.1	<.0001
Error	1429	4377221	3063.14		
Corrected Total	1439	33296863			

R-Square	Coeff Var	Root MSE	WIP Mean
0.869	24.5	55.3456	225.9037

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Shortcut Cost/WIP Cost(Ω)	3	963365.6	321121.9	104.8	<.0001
Utilization (ρ_{LCMHS})	2	21381919	10690959	3490	<.0001
Turntable Turn Time (t)	2	13352.99	6676.49	2.18	0.114
Optimization Criteria (θ)	1	19946.72	19946.72	6.51	0.011
Shortcut Criteria (S)	1	6524756	6524756	2130	<.0001
Scenario (θS)	1	16302.16	16302.16	5.32	0.021

To summarize:

- The overall fit of the model is significant and accounts for 86.9% of the error
- Ω has a significant effect on the WIP for the solutions of the LLDP test problems
- ρ_{LCMHS} has a significant effect on the WIP for the solutions of the LLDP test problems
- t does not have a significant effect on the WIP for the solutions of the LLDP test problems
- Θ has a significant effect on the WIP for the solutions of the LLDP test problems
- S has a significant effect on the WIP for the solutions of the LLDP test problems
- ΘS has a significant effect on the WIP for the solutions of the LLDP test problems

The next step is to compare the means of the dependent variable (WIP) for each of the independent variables

6.4.2 Comparison of Means

Here, for each main effect the comparison of means tests (REGWQ and Tukeys multiple comparison test) elucidates any difference in the means of the dependent variable (WIP) for each level of the main effect, thereby clarifying the influence (or lack thereof) of the main effects on the dependent variable (WIP); while controlling for Type I and Type II error.

6.4.2.1 Variable: Shortcut Cost / WIP Cost (Ω)

In Table 6.28, the dependent variable WIP is compared across the different levels of the main effect Ω using REGWQ and Tukeys multiple comparison test. It should be noted that means with the same letter (under the grouping columns) are not significantly different. The main effect 'Ω' is introduced to test if there is a significant difference in the WIP on the LLMF for different levels of Ω.

Table 6.28: REGWQ and Tukeys multiple comparison test for Ω for the LLDP

			Grouping*	
Ω	N	Mean WIP	REGWQ	Tukey
50	360	267.05	A	A
10	360	228.88	B	B
1	360	204.67	C	C
0.1	360	203.02	C	C

Note: These tests control the Type I experiment-wise error rate
* Means with the same letter are not significantly different

To summarize:

- When $\Omega \leq 1$ there is no significant difference in the WIP of the solutions
- When $\Omega > 1$ there is significant difference in the WIP of the solutions.

- As the ratio of the cost of the shortcut to the cost of the WIP increases, the WIP of the best solutions increases.

6.4.2.2 Variable: Utilization of Conveyor (ρ_{LCMHS})

In Table 6.29, the dependent variable WIP is compared across the different levels of the main effect ρ_{LCMHS} using REGWQ and Tukeys multiple comparison test. It should be noted that means with the same letter (under the grouping columns) are not significantly different. The main effect 'ρ_{LCMHS}' is introduced to test if there is a significant difference in the WIP on the LLMF for different levels of ρ_{LCMHS}.

Table 6.29: REGWQ and Tukeys multiple comparison test for ρ_{LCMHS} for the LLDP

			Grouping*	
ρ_{LCMHS}	N	Mean WIP	REGWQ	Tukey
0.85	480	267.05	A	A
0.5	480	228.88	B	B
0.15	480	203.02	C	C

Note: These tests control the Type I experiment-wise error rate
* Means with the same letter are not significantly different

To summarize:

- There is a significant difference in the WIP of the solutions for the different levels of ρ_{LCMHS}

- As ρ_{LCMHS} increases the WIP of the best solutions increases

6.4.2.3 Variable: Turntable Turn Time (*t*)

In Table 6.30, the dependent variable WIP is compared across the different levels of the main effect *t* using REGWQ and Tukeys multiple comparison test. It should be noted that means with the same letter (under the grouping columns) are not significantly different. The main effect 't' is introduced to test if there is a significant difference in the WIP on the LLMF for different levels of 't'.

Table 6.30: REGWQ and Tukeys multiple comparison test for *t* for the LLDP

			Grouping*	
t	N	Mean WIP	REGWQ	Tukey
15	480	229.92	A	A
7	480	225.73	A	A
0	480	222.27	A	A

Note: These tests control the Type I experiment-wise error rate
* Means with the same letter are not significantly different

To summarize:

- There is no significant difference in the WIP of the solutions for the different levels of *t*

6.4.2.4 Variable: Optimization Criteria (θ)

In Table 6.31, the dependent variable WIP is compared across the different levels of the main effect θ using REGWQ and Tukeys multiple comparison test. It should be noted that means with the same letter (under the grouping columns) are not significantly different. The main effect 'θ' is introduced to test if there is a significant difference in the WIP on the LLMF when using the WIP (θ = 1) as opposed to the total distance travelled (θ = 2); as a factor in the minimizing function for the MFLP.

Table 6.31: REGWQ and Tukeys multiple comparison test for θ for the LLDP

			Grouping*	
θ	N	Mean WIP	REGWQ	Tukey
2	720	229.63	A	A
1	720	222.31	B	B

Note: These tests control the Type I experiment-wise error rate
* Means with the same letter are not significantly different

To summarize:

- There is a significant difference in the WIP of the solutions for the different levels of θ
- As θ increases the WIP of the best solutions increases, i.e.,
    - o Using the WIP (θ = 1), as opposed to the total distance travelled (θ = 2), as a factor in the minimizing

function for the MFLP yields LLMFs with lower WIP (less congestion)

6.4.2.5 Variable: Shortcut Selection Criteria (*S*)

In Table 6.32, the dependent variable WIP is compared across the different levels of the main effect *S* using REGWQ and Tukeys multiple comparison test. It should be noted that means with the same letter (under the grouping columns) are not significantly different. The main effect '*S*' is introduced to test if there is a significant difference in the WIP on the LLMF when using the combined method to determine the shortcuts (*S* = 1) as opposed to separate method to determine the shortcuts (*S* = 2).

Table 6.32: REGWQ and Tukeys multiple comparison test for *S* for the LLDP

			Grouping*	
S	N	Mean WIP	REGWQ	Tukey
2	720	293.35	A	A
1	720	158.59	B	B

Note: These tests control the Type I experiment-wise error rate
* Means with the same letter are not significantly different

To summarize:

- There is a significant difference in the WIP of the solutions for the different levels of *S*
- As *S* increases the WIP of the best solutions increases, i.e.,

- o Using the combined method to determine the shortcuts (S = 1), as opposed to separate method to determine the shortcuts (S = 2), yields LLMFs with lower WIP (less congestion)

6.4.2.6 Variable: Scenario (*θS*)

In Table 6.33, the dependent variable WIP is compared across the different levels of the main effect θS using REGWQ and Tukeys multiple comparison test. It should be noted that means with the same letter (under the grouping columns) are not significantly different. The main effect 'θS' is introduced to test if there is a significant difference in the WIP on the LLMF for different levels of 'θS', i.e., for the different scenarios as described in § 5.2.2 and summarized in Table 5.10.

Table 6.33: REGWQ and Tukeys multiple comparison test for θS for the LLDP

			Grouping*	
θS	N	Mean WIP	REGWQ	Tukey
4	360	293.57	A	A
2	360	293.12	A	A
3	360	165.68	B	B
1	360	151.50	C	C

Note: These tests control the Type I experiment-wise error rate
* Means with the same letter are not significantly different

To summarize:

- There is a significant difference in the WIP of the solutions for the some of the different levels of *θS*
- *θS = 1* has the *lowest* the WIP of the best solutions
    - Scenario E yields LLMFs with the least WIP (least congestion) followed by Scenario G.

Notably, Scenario F and Scenario H yield LLMFs with similar WIP levels.

6.4.3 Evaluation of Hypotheses

The results from the test problems for the LLDP show that the proposed methodology outperforms traditional methods used for the MFLP. Θ, S, and ΘS are introduced to measure the effect of the choice of: the optimization criteria (Θ), the shortcut selection criteria (S), and the interaction of Θ and S (ΘS)

Consider the main effect ΘS. The results from the GLM analysis, as presented in § 6.4.2.6, indicate that there is a significant difference in the resultant WIP of the solutions for the different scenarios. Scenario E has the lowest WIP followed by Scenario G and Scenario E is significantly different from Scenario G. Although both Scenario F and Scenario H are significantly different from Scenario E and Scenario G respectively, they are not significantly different from each other.

Given these outcome, one can make the following statements:

- $H1_0$ (Null hypothesis for Hypothesis Test 1 as presented in § 5.2.8.1) *is rejected*.
- $H2_0$ (Null hypothesis for Hypothesis Test 2 as presented in § 5.2.8.2) *is rejected*.
- $H3_0$ (Null hypothesis for Hypothesis Test 3 as presented in § 5.2.8.3) *is rejected*.
- $H4_0$ (Null hypothesis for Hypothesis Test 4 as presented in § 5.2.8.4) *is rejected*.
- $H5_0$ (Null hypothesis for Hypothesis Test 5 as presented in § 5.2.8.5) *is not rejected*.

7 DISCUSSION

7.1 Expected WIP at the Input Stations of the Conveyor

Although the proposed analytical estimate is not general it performs extremely well for situations that have Markovian arrival processes, i.e., when the time between the arrivals of loads to the system is modeled by the exponential distribution. This outcome is to be expected as the proposed analytical estimate is built using Welch (1964); an M/G/1 approximation that assumes loads arrive according to a Markov process. Ideally, a G/G/1 approximation for the service at the input stations would work best since it would account for any interarrival time variability and could thereby provide better estimates of the total WIP at the input stations. However, currently there is no G/G/1 formulation that takes into account the queueing process in which the first customer of each busy period receives exceptional service, akin to the Type 1 and Type 2 service distributions as described in § 3.2.2.

The proposed methodology also performs extremely well when the utilization of the conveyor is less than 0.5 for any arrival process. This is an interesting artifact of the results, as for lower utilizations of the conveyor system it implies that the interarrival time variability does not have much effect on the total WIP at the input stations of a conveyor. An explanation for this is that at lower utilizations, the loads arriving to the conveyor do not have to wait for long at the input stations as the likelihood of encountering an unoccupied window on the conveyor is high. The effect of the interarrival time variability will be more prevalent in situations where the loads have to wait at the input stations as a result of encountering many unoccupied windows on the conveyor (when the conveyor is busy, i.e. the utilization of the conveyor is high.) This is also reflected in the simulation results for the total WIP at the input stations which show significantly lower total WIP for levels of utilization less than 0.5 in comparison to utilization levels greater than 0.5. Also, for the different levels of interarrival time variability, for utilization levels greater than 0.5, there is a measureable difference in the total WIP at the input stations. Again, a G/G/1 approximation could provide for better estimates of the total WIP at the input stations.

Overall, from a practical standpoint the proposed analytical estimate of the total WIP at the input stations around a conveyor performs rather well; given that the utilization of the conveyor is less than 0.9, the average absolute relative error of the analytical estimate is 5.59%. Also, the proposed methodology for the analytical estimate is the first to develop a distribution for the service at the input stations to the conveyor.

7.2 Looped Layout Design Problem

For the testing of the LLDP, the outcomes of the utilization of the conveyor and the ratio of the cost of the shortcut to the cost of the WIP (Ω) were as expected. As with most manufacturing systems, when the utilization of the system increases the overall WIP in the system increases. With regards to Ω, as Ω increases the relative cost of adding shortcuts increases, hence fewer shortcuts are added. As a result of there being fewer shortcuts, the overall WIP in the system is higher. This is an interesting outcome although this result is intuitive; as a result of adding the shortcut the travelling WIP on the conveyor is reduced thereby reducing the overall WIP on the conveyor, and the converse also hold true.

Next, in the analysis of the turntable turntime, the results show that *t* had no measureable effect on the overall WIP of the system. This is a very interesting outcome. It is important to note that in prior testing where *t* was considered to be significant (Hong et al., 2011; Johnson et al., 2009; Nazzal et al., 2010, 2008), the layouts of the facilities upon which simulation studies were performed were not optimized. Therefore, for those simulation studies the utilization of the turntables was high. Hence, it was incorrectly perceived that the turntime of the turntables had an impact on the level of the overall WIP on the LCMHS.

Now, as a result of finding better layouts (from the GA solution procedure) there is less WIP on the conveyor. Therefore, utilization of the turntables is lower (since the flow of loads on LLMF is more streamlined.) Hence, the actual impact of the turntable turntime is not significant. This interesting outcome can have a significant impact on future considerations in the design process of LLMFs.

Table 7.1: Number of Design with Average Miminum WIP for each test problem

	# of Designs with Average Minimum WIP		
	Combined	Separate	Total
WIP	32	2	34
Distance	2	0	2
Total	34	2	36

Consider the optimization criteria (Θ), the results from the analysis show that the resultant WIP when using the WIP as the optimization criteria is significantly different from and lower than the resultant WIP when using the total distance travelled. The best solutions determined by using the WIP as the optimization criteria are better equipped at selecting the layout that results in the lowest WIP. The best layouts determined by using the distance-based methods do not guarantee the lowest WIP. For individual test problems, it has been observed that systems with the lowest WIP do not always have the lowest total distance travelled among the set of best solutions for the respective test problem. As it can be seen from Table 7.1, for the 36 test problems[3], 34 out of the 36 problems had the lowest average minimum WIP (for the 10 replications) from the solutions determined by using the WIP as the optimization criteria.

For the shortcut selection criteria (S), the results from the analysis show that the resultant WIP when using the 'combined' design method as the shortcut selection criteria is significantly lower than the resultant WIP when using the separate design method. As proposed, the combined method for determining the shortcuts is akin to a global search method and the magnitude of the difference in the WIP between the combined and separate methods for determining the shortcuts support this claim. Furthermore, as it can be seen from Table 7.1, for the 36 test problems, 34 out of the 36 problems had the lowest average mini-

[3] For each of the 36 test problems there are four scenarios, and for each scenario there are 10 replications.

mum WIP (for the 10 replications) from the solutions determined by using the combined method as the selection criteria.

Of all the scenarios tested, Scenario E which represents the proposed methodology had the best results while Scenario H which represents the traditional methodology had the worst results. The combined effect of using the WIP as the optimization criteria and using the combined method as the shortcut selection criteria yielded layouts with the lowest congestion. As it can be seen from Table 7.1, for the 36 test problems, 32 out of the 36 problems had the lowest average minimum WIP (for the 10 replications) from the solutions determined by using Scenario E while *none* of the test problems had the lowest average minimum WIP from the solutions determined by using Scenario H. The outcomes of the testing overwhelmingly support the use of the proposed methodology.

8 CONCLUDING REMARKS

8.1 Summary of Proposed Methodology

Traditionally, manufacturing facility layout problem methods aim at minimizing the total distance traveled, the material handling cost, or the time in the system (based on distance traveled at a specific speed). Bozer & Hsieh (2005) suggests that for a LLMF, the most appropriate design criterion for the LLDP with a LCMHS would be to minimize the total WIP on the LCMHS and the input stations for all the cells in the LLMF. This dissertation research proposed an analytical model to estimate the total work in process at the input stations to the closed looped conveyor. Further, a methodology was proposed to solve the looped layout design problem for a looped layout manufacturing facility with a looped conveyor material handling system with shortcuts using a system performance metric, i.e. the work in process (WIP) on the conveyor and at the input stations to the conveyor, as a factor in the minimizing function for the facility layout optimization problem; which is solved heuristically using a permutation genetic algorithm.

Traditionally, the optimal layout of a facility is first determined. After some time of operation, usually if needed, the best set of shortcuts is determined to alleviate congestion in the LLMF as described by Hong, Johnson, Carlo, Nazzal, and Jimenez (2011). It is the contention of the proposed research that the aforementioned two-step process yields a sub-optimal solution. The proposed methodology also argues the case for determining the shortcut locations across the conveyor simultaneously (while determining the layout of the stations around the loop) versus the traditional method which determines the shortcuts sequentially (after the layout of the stations has been determined).

8.2 Summary of Findings

The findings presented summarize those from § **Error! Reference source not found.**.

- The proposed methodology (using the WIP as a factor in the minimizing function for the facility layout while simultaneously solving for the shortcuts) yields a facility layout which is less congested than a facility layout generated by the traditional methods
  - Of all methods tested, the proposed methodology performed the best in the testing while the traditional methodology performed the worst

- For the LLDP, using the WIP as the optimization criteria has a significant effect on lowering the overall WIP in the LLMF
- For the LLDP, using the combined method to determine the shortcuts has a significant effect on lowering the overall WIP in the LLMF
- Using, the combined method to determine the shortcuts has the greater impact on lowering the overall WIP in the LLMF when compared to the separate method of designing the Layout and then optimizing the shortcut locations
- The turntable turn time does not have an effect on the overall WIP of the system as a result of the lowered utilization of the turntables
- Statistically, the proposed analytical estimate provides reliable estimates for the total WIP at the input stations to a LCMHS for Markovian arrival processes if the utilization of the conveyor is less than 0.9
- Statistically, the proposed analytical estimate provides reliable estimates for the total WIP at the input stations to a LCMHS for any arrival processes if the utilization of the conveyor is less than 0.5
- Practically, the proposed analytical estimate provides reliable estimates for the total WIP at the input stations to

a LCMHS for any arrival processes while the utilization of the conveyor is less than 0.75 with an average relative absolute relative error of 4.47% which is well within the acceptable range of error as presented in past studies

8.3 Summary of Contributions

The proposed research mainly contributes to the field of manufacturing facility layout with other contributions to the field of conveyor systems analysis. The contributions are as listed below:

- The proposed methodology presents, tests and validates the use of a combined solution algorithm (solve for the Layout and shortcuts simultaneously) versus the traditional sequential two-step process
    - The proposed methodology uses the WIP on the conveyor and the WIP at the input stations to the conveyor as a factor in the minimizing function for the FLP for MFs with a LMCHS
    - The proposed methodology uses the combined method to determine the shortcuts at each iteration for the FLP for MFs with a LMCHS
    - The proposed methodology uses a custom tailored permutation genetic algorithm to solve the LLDP

- The proposed methodology presents, tests and validates an analytical estimate for the total WIP at the input stations of the conveyor
  - the proposed methodology for the analytical estimate develops a distribution for the service times at the input stations to the conveyor where the service time is modeled as the residual conveyor cycle time and the time the load waits for the first unoccupied window
- Prior work from Nazzal, Jimenez, Carlo, Johnson, and Lasrado (2010) is used in the proposed methodology to estimate the WIP on a conveyor with shortcuts
  - The proposed methodology presents a multi-phased approach that estimates the WIP on the conveyor and across the shortcuts of the conveyor
- Prior work from Johnson, Carlo, Jimenez, Nazzal, and Lasrado (2009) is used to find the best set of shortcuts on the conveyor
  - The greedy heuristic as presented is extremely quick at finding configurations of near optimal configurations of shortcuts around the LCMHS

8.4 Implications to Practitioners

The findings of the proposed methodology for both, the LLDP and the analytical estimate for the total WIP at the input stations have significant implications to practitioners.

For the LLDP:

- The proposed methodology enhances the transparency of the LLMF while determining the layout
  - o With the traditional methodology the practitioner may determine a layout for a facility but has no information about the operational performance of the LLMF
  - o In addition to determining the layout of the LLMF, the proposed methodology also presents the practitioner with useful information about the operational performance of the LLMF for each considered layout. System performance measures such as time in system, time in queue, etc. can easily be derived using Little’s Law if the mean WIP is known
- The finding that the turntable turntime does not affect the overall WIP in the LLMF is of significance
  - o In an industry such as semiconductor manufacturing, one of the key elements of the manufacturing process is to reduce the vibrations on the conveyor so as to

maintain the integrity of the semiconductor chips being manufactured. Since the turntime is of no consequence to the overall WIP in the LLMF, practitioners can design facilities with slower turntable turn rates to reduce the possibility of vibrations along the LCMHS.

- As the findings of this research have shown, it greatly benefits the practitioner to include shortcuts (if financially feasible) in the design of the layout of the LLMF from the onset if lowering congestion is important

For the analytical estimate of the total WIP at the input station around the conveyor:

- An interesting outcome of the study is that no matter what the combination of arrival rate or speed of the conveyor, for a particular level of utilization (that is an outcome of a given arrival rate and the speed of the conveyor); the expected WIP around the conveyor and at the input stations around the conveyor is the same
    - In the testing of WIP estimates this finding greatly simplifies the design of experiment by reducing the number of variables that need to be varied

- It is important for the practitioner to consider two key parameters of the LCMHS, viz., the utilization of the LCMHS and the arrival process to the LCMHS
    - In environments with lower utilization levels (less than 0.5) and arrival process that are close to the Markov process the analytical estimates provides reliable results.

8.5 Future Work

For the LLDP:

- Adapt the proposed methodology to include the WIP from production system so as to capture the WIP in the *entire manufacturing facility*
- Adapt the proposed methodology to consider blocking and recirculation of loads in the estimate for the overall WIP around the conveyor
    - In most real world scenarios the assumption that queues have infinite length is unrealistic since most loading and unloading stations have finite buffers
- The proposed methodology considers a rectangular closed loop layout.

- Future work will involve the modification of this methodology to include non-standard closed loop facility shapes
- Future work will involve the modification of this methodology to include non-standard open field facility layout

- Currently, all the shortcuts by design are orthogonal to the LCMHS connecting one side of the conveyor to the other, future work would adapt the proposed methodology to include
  - Non-orthogonal shortcuts that could provide for
    - connecting one side of the conveyor to the other
    - bypassing stations on the same side of the conveyor

For the analytical estimate of the total WIP at the input stations:

- Adapt the current M/G/1 formulation to a G/G/1 queueing formulation that takes into account the queueing process in which the first customer of each busy period receives exceptional service

8.6 Conclusion

A particular choice of a facility Layout can have a significant impact on the ability of a company to maintain lower operational expenses. Furthermore, a poor Layout can result in high material handling costs, excessive work-in-process (WIP), and low or unbalanced equipment utilization. Most traditional MFLP formulations ignore the impact of the facility layout on the operational performance of the MF i.e. the work-in-process (WIP), the throughput, or the cycle time.

The proposed methodology aims at minimizing the WIP on the LLMF by using the WIP on the conveyor and the WIP at input stations of the conveyor as a factor in the minimizing function for the facility layout optimization problem while simultaneously solving for the best set of shortcuts. The proposed methodology is tested on a virtual 300mm Semiconductor Wafer Fabrication Facility with a looped conveyor material handling system with shortcuts. The results show that the facility layouts generated by the proposed methodology have significantly less congestion than facility layouts generated by traditional methods.

The proposed methodology presented an analytical estimate for the total WIP at the input stations around the conveyor. The validation of the developed analytical estimate of the work in process at the input stations reveals that the proposed methodology works extremely well for systems with Markovian Arrival Processes.

At the start of this document it was stated that,

> "every company is looking for an advantage over its peers; an important practical question is how do companies create this competitive advantage in terms of creating value?"

As presented, the proposed methodology for determining the layout for a MF with a LCMHS with shortcuts best positions the MF to lower its operational expenses by incorporating material handling decisions at the development stage. The result of the proposed facility layout planning strategy is a facility layout with less congestion that has the potential to drastically reduce the operational expenses of a MF, thereby creating value, in terms of savings in operational expenses, which in turn provides the company with a competitive advantage over its peers.

APPENDIX A: FROM-TO MATRIX FOR LAYOUT X

	To																							
From	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0	0	0	0	0	0	7.87	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0.92	0	0.73	0	0	1.12	0.25	0.34	0	0	0	0.67	0	0	0	0	0	0	1.6	3.63	0.64	0.62
3	1.44	1.01	0	1.06	1.29	0.26	0.51	1.46	1.36	0.48	0	0	0.22	0.03	0.06	0	0.46	0.36	0	1.28	0.41	0.49	0.27	1.27
4	2.29	0	1.16	0	1.15	0.35	0.79	0	0	0	0	0	0.22	0	0.17	0	0.21	0	0	1.94	0.05	0	0	2.16
5	1.45	0.57	0.64	0.63	0	0.23	0.47	3.54	0.32	1.08	0	0	0.23	0.1	0.07	0	0.42	0.37	0	0.89	0.63	0.89	0.29	0.68
6	0	0	0.52	0.49	0.14	0	0.63	0	0	0.81	0	0	1.17	0	0.41	0	0	0.46	1.24	0.79	0	0	0	0.46
7	0	0	0	0	0	0	0	0	0	2.6	0	0	0	0	0	0	0	0	0	10.6	0	0	0	0
8	0	0.01	0	0	0	0	0	0	4.08	0.98	0	0	0	0	0	0	0	0	0	0	1.91	3.19	0	0
9	0	0.01	0.01	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.02	4.92	0	0
10	0	0	0.01	0	0	0	0	0.02	1.28	0	0	0	0	0	0	0	0	0	0	2.55	2.48	1.74	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.01	4.93	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	2.73	2.47	1.07	2.99	0.95	0	0	0	0.27	0	0	0	0.05	0.13	0	0	1.35	2.12	0.31	0.09	0.21	0.04	0.44
14	0	0.49	1.6	0	0.47	0	0	0	0	0	0	0	0.13	0	0	0	0.17	0.11	0	0	0.63	1.26	4.51	0.27
15	0	0	0	0	0	0.68	0.65	0	0	0	0	0	0	0	0	3.32	0	0	0.68	0	0	0	0	1.39
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.32	0	0	0	0	0	0	0	0	6.61
17	0	0	2.6	0	0	0	0	0	0	0	0	0	5.36	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0.55	1.04	0.34	1.78	0	0	0	0.13	7.6	0	0.65	0	0.05	0	0	0	0.6	0.14	1.65	0	0	1.56
19	0	0	0	0	0	1.65	0	0	0	0	0	0	4.83	0	0	0	0	1.75	0	0	3.52	0	0.99	1.85
20	2.1	0	0.49	3.65	1.34	0.34	2.11	0	0	0	0	0	0.21	0	1.52	0	0.26	2.65	7.9	0	0.06	0	0	0.84
21	0.64	0.58	0.23	0.17	0.44	0.42	0.2	1.69	0.28	0.51	1.65	0	0.7	3.05	0.94	2.47	0.44	3.86	1.36	0.35	0	2.07	0.86	0.44
22	0	1.84	0.47	0	1.11	0	0	2.35	0.4	0.72	0	0	0	4.98	0	4.15	1.03	4.73	0	0	2.39	0	1.11	0.02
23	0	2.9	0.19	0	1.93	0	0	0	0	0	0	0	0.38	0.58	0	0	0.15	0.09	0	1.35	0.4	0.66	0	0.45
24	0	0.4	1.87	2.39	1.55	0.46	0	0	0	0.14	0	0	1.13	0.18	0.06	0	4.86	0.32	0.67	1.86	1.52	1.28	0.38	0

APPENDIX B: FROM-TO MATRIX FOR LAYOUT Y

	To																							
From	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	0	0	0	0	0	8.23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0.95	0	0.71	0	0	1.16	0.28	0.32	0	0	0	0.67	0	0	0	0	0	0	1.65	3.82	0.67	0.7
3	1.57	1.08	0	0.97	1.37	0.53	0	1.6	1.5	0.49	0.23	0	0.05	0.43	0.28	0	0	0	0.18	1.13	0.39	0.46	0.54	1.3
4	2.3	0	1.19	0	1.18	0.75	0	0	0	0	0.33	0	0.17	0.24	0	0	0	0	0.25	1.13	0.04	0	0.7	2.32
5	1.47	0.6	0.66	0.58	0	0.56	0	3.66	0.31	1.05	0.18	0	0.09	0.63	0.2	0	0	0	0.3	0.85	0.68	1	0.63	0.74
6	0	0	0.53	0.51	0.19	0	13.8	0.8	0	1.25	0.31	0	0.84	0	0.4	0	0	1.61	0.34	0.13	0	0	0.86	0.53
7	0	0	0	0	0	1.41	0	1.47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10.9	0
8	0	0	0	0	0	0	0	0	4.21	4.29	0	0	0	0	0	0	0	0	0	0	2.05	3.26	0	0
9	0	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.17	5.12	0	0
10	0	0	0.01	0	0	0	0	0.39	1.27	0	9.74	0	0	0	0	0	0	0	0	0	1.1	3.3	2.63	0
11	0	0	0	0	0	4.1	0	0	0	0.06	0	0	0	0	0	0	0	0	0	0	2.97	5.36	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	2.87	2.53	1.06	3.13	0.42	0	0.3	0	0	0.6	0	0	0.04	4.41	0	0	2.25	1.55	1.08	0.08	0.16	0.34	0.51
14	0	0.57	1.79	0	0.55	0	0	0	0	0	0	0	0.07	0	4.31	0.11	8.47	0	0	0.09	0.61	1.31	0.29	0.31
15	0	0	0	0	0	1.28	0	0	0	0	0	0	1.47	0	0	0	3.43	0.77	0	0	1.45	0	8.25	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	8.45	0	0	3.5	0	0	0	6.84	0	0	0
17	0	0	2.8	0	0	0	0	0	0	0	0	0	0	0.09	3.44	10.4	0	0	5.58	0	0	0	0	0
18	0	0	0.58	1.04	0.3	0.16	0	0.13	0	7.97	1.66	0	0.33	0	0.07	0	0	0	12.9	0.13	3.49	0	0.1	0.21
19	0	0	0	0	0	1.78	0	0	0	0	0	0	14.5	0	0.93	0	0	1.85	0	0	0	1.39	0	1.83
20	2.17	0	0.51	3.88	1.35	2.07	0	0	0	0	0.35	0	1.58	0.25	0	0	0	20	0.26	0	1.76	0	8.9	0.76
21	0.63	0.61	0.24	0.17	0.5	0.5	0	1.65	0.31	2.31	0.15	0	1.65	0.51	0.8	2.98	2.53	1.73	0	3.98	0	2.05	0.2	10.1
22	0	2.03	0.54	0	1.08	0	0	2.55	0.39	0.71	0	0	0	1.05	1.11	5.36	4.31	0	0	4.78	5.39	0	0.03	0.04
23	0	2.97	0.18	0	2.01	0	0	0	0	0	0	0	0.38	0.78	0.35	0	0	0	0	28.4	0.39	0.74	0	0.45
24	0	0.38	1.64	2.38	1.78	0.24	0	0.14	0	0	0.3	0	0.22	5.21	0.33	0	0	0.79	0.85	2.22	1.62	1.36	0.35	0

APPENDIX C: RESULTS FROM WIP AT INPUT STATIONS TESTING

For Layout X

			For Layout X Total WIP at Input Stations From										
			Simulation Rep										Analytical
Test	Rho	SCV	1	2	3	4	5	6	7	8	9	10	Estimate
1	0.15	0.5	0.095	0.097	0.097	0.096	0.094	0.095	0.093	0.095	0.095	0.097	0.097
2	0.3	0.5	0.474	0.473	0.474	0.474	0.475	0.471	0.471	0.475	0.472	0.474	0.507
3	0.45	0.5	1.478	1.466	1.484	1.470	1.472	1.467	1.480	1.497	1.484	1.480	1.602
4	0.6	0.5	3.949	3.981	3.948	3.985	3.958	3.945	3.977	3.951	3.967	3.984	4.480
5	0.75	0.5	11.219	11.198	11.207	11.275	11.290	11.214	11.143	11.264	11.260	11.290	13.498
6	0.9	0.5	52.709	52.361	52.828	53.767	53.837	52.093	53.174	53.167	51.539	53.546	59.393
7	0.15	0.77	0.095	0.096	0.097	0.096	0.096	0.095	0.095	0.096	0.097	0.097	0.097
8	0.3	0.77	0.482	0.482	0.480	0.480	0.479	0.477	0.480	0.477	0.474	0.479	0.507
9	0.45	0.77	1.523	1.524	1.526	1.523	1.514	1.526	1.523	1.518	1.518	1.522	1.602
10	0.6	0.77	4.223	4.204	4.190	4.200	4.187	4.200	4.190	4.186	4.193	4.179	4.480
11	0.75	0.77	12.667	12.567	12.597	12.638	12.576	12.634	12.658	12.685	12.695	12.519	13.498
12	0.9	0.77	68.852	68.176	69.430	70.506	67.858	70.132	70.540	68.940	67.450	68.779	59.393
13	0.15	1	0.096	0.096	0.094	0.098	0.095	0.095	0.096	0.097	0.098	0.097	0.097
14	0.3	1	0.481	0.480	0.481	0.483	0.482	0.483	0.479	0.481	0.480	0.485	0.507
15	0.45	1	1.560	1.552	1.562	1.564	1.569	1.564	1.563	1.555	1.556	1.562	1.602
16	0.6	1	4.426	4.397	4.431	4.377	4.415	4.420	4.406	4.428	4.423	4.416	4.480
17	0.75	1	13.893	13.756	13.880	13.928	13.716	13.885	13.852	13.785	13.954	13.809	13.498
18	0.9	1	84.675	82.300	83.888	81.491	85.873	81.907	81.043	84.559	83.696	84.548	59.393
19	0.15	1.23	0.096	0.097	0.097	0.097	0.101	0.098	0.100	0.098	0.099	0.097	0.097
20	0.3	1.23	0.482	0.489	0.487	0.486	0.489	0.487	0.484	0.489	0.486	0.487	0.507
21	0.45	1.23	1.611	1.595	1.608	1.611	1.607	1.592	1.597	1.603	1.618	1.627	1.602
22	0.6	1.23	4.597	4.584	4.606	4.570	4.624	4.626	4.641	4.637	4.622	4.641	4.480
23	0.75	1.23	15.057	14.875	15.104	15.035	15.058	15.140	15.132	15.093	15.003	14.881	13.498
24	0.9	1.23	96.440	96.191	103.152	95.726	94.651	97.005	99.316	98.081	95.823	97.644	59.393
25	0.15	1.5	0.099	0.099	0.099	0.101	0.098	0.100	0.100	0.098	0.101	0.098	0.097
26	0.3	1.5	0.493	0.492	0.494	0.495	0.490	0.493	0.496	0.496	0.491	0.491	0.507
27	0.45	1.5	1.695	1.669	1.694	1.698	1.680	1.669	1.699	1.679	1.669	1.692	1.602
28	0.6	1.5	4.900	4.863	4.857	4.887	4.850	4.840	4.869	4.868	4.895	4.883	4.480
29	0.75	1.5	16.644	16.303	16.513	16.407	16.451	16.580	16.346	16.631	16.523	16.529	13.498
30	0.9	1.5	115.708	108.513	109.759	114.271	112.672	112.827	113.684	113.119	112.035	116.096	59.393

For Layout Y

Test	Rho	SCV	For Layout Y Total WIP at Input Stations From Simulation Rep 1	2	3	4	5	6	7	8	9	10	Analytical Estimate
1	0.15	0.5	0.099	0.099	0.099	0.098	0.097	0.100	0.098	0.100	0.098	0.097	0.100
2	0.3	0.5	0.490	0.489	0.491	0.487	0.489	0.492	0.493	0.492	0.491	0.489	0.524
3	0.45	0.5	1.517	1.516	1.521	1.519	1.516	1.517	1.517	1.518	1.522	1.519	1.653
4	0.6	0.5	4.051	4.042	4.081	4.054	4.069	4.057	4.056	4.068	4.085	4.060	4.604
5	0.75	0.5	11.676	11.594	11.713	11.677	11.665	11.617	11.652	11.674	11.723	11.714	13.774
6	0.9	0.5	57.277	57.915	57.463	56.322	56.706	57.818	57.625	57.616	57.006	57.160	59.695
7	0.15	0.77	0.100	0.099	0.099	0.098	0.097	0.101	0.099	0.101	0.100	0.099	0.100
8	0.3	0.77	0.496	0.490	0.494	0.495	0.493	0.494	0.493	0.496	0.494	0.497	0.524
9	0.45	0.77	1.602	1.602	1.588	1.584	1.581	1.574	1.593	1.588	1.599	1.588	1.653
10	0.6	0.77	4.352	4.350	4.373	4.350	4.323	4.318	4.350	4.351	4.356	4.372	4.604
11	0.75	0.77	13.103	13.170	13.201	13.168	13.225	13.176	13.311	13.248	13.222	13.036	13.774
12	0.9	0.77	76.374	73.257	75.199	76.089	73.622	73.610	75.735	74.011	75.996	73.973	59.695
13	0.15	1	0.101	0.101	0.100	0.100	0.100	0.098	0.102	0.101	0.100	0.099	0.100
14	0.3	1	0.501	0.500	0.503	0.502	0.500	0.501	0.502	0.502	0.501	0.502	0.524
15	0.45	1	1.634	1.636	1.642	1.640	1.625	1.629	1.650	1.638	1.640	1.630	1.653
16	0.6	1	4.599	4.623	4.616	4.596	4.593	4.580	4.625	4.642	4.637	4.607	4.604
17	0.75	1	14.550	14.665	14.494	14.439	14.530	14.628	14.686	14.555	14.505	14.516	13.774
18	0.9	1	91.459	89.476	89.916	88.549	92.095	92.305	91.087	90.611	90.162	87.213	59.695
19	0.15	1.23	0.101	0.100	0.100	0.102	0.102	0.100	0.101	0.101	0.100	0.099	0.100
20	0.3	1.23	0.508	0.506	0.505	0.504	0.506	0.508	0.506	0.509	0.507	0.509	0.524
21	0.45	1.23	1.703	1.716	1.673	1.674	1.684	1.708	1.705	1.700	1.710	1.717	1.653
22	0.6	1.23	4.889	4.843	4.877	4.862	4.857	4.835	4.825	4.832	4.852	4.867	4.604
23	0.75	1.23	16.034	15.779	16.043	15.913	15.834	15.893	15.837	15.942	15.960	16.007	13.774
24	0.9	1.23	106.384	104.591	105.829	105.308	106.264	104.023	102.775	110.051	106.263	104.769	59.695
25	0.15	1.5	0.102	0.100	0.101	0.101	0.102	0.100	0.100	0.102	0.101	0.101	0.100
26	0.3	1.5	0.526	0.525	0.527	0.514	0.525	0.527	0.529	0.524	0.527	0.527	0.524
27	0.45	1.5	1.777	1.767	1.768	1.763	1.776	1.752	1.764	1.776	1.781	1.773	1.653
28	0.6	1.5	5.156	5.132	5.195	5.152	5.150	5.175	5.162	5.163	5.203	5.150	4.604
29	0.75	1.5	17.623	17.483	17.577	17.401	17.464	17.539	17.413	17.487	17.546	17.635	13.774
30	0.9	1.5	125.878	120.425	122.062	120.331	123.405	120.128	119.663	122.105	124.456	122.940	59.695

For Layout Z

Test	Rho	SCV	For Layout Z Total WIP at Input Stations From Simulation Rep 1	2	3	4	5	6	7	8	9	10	Analytical Estimate
1	0.15	0.5	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.104
2	0.3	0.5	0.513	0.513	0.516	0.512	0.513	0.511	0.512	0.512	0.512	0.516	0.544
3	0.45	0.5	1.747	1.749	1.743	1.744	1.749	1.751	1.748	1.751	1.753	1.749	1.725
4	0.6	0.5	4.586	4.611	4.610	4.591	4.591	4.584	4.604	4.614	4.598	4.603	4.872
5	0.75	0.5	13.354	13.271	13.410	13.428	13.307	13.271	13.324	13.387	13.479	13.375	15.058
6	0.9	0.5	62.129	60.944	61.030	62.463	62.100	61.152	60.774	61.373	62.706	62.751	68.773
7	0.15	0.77	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.104
8	0.3	0.77	0.515	0.513	0.513	0.519	0.516	0.517	0.511	0.510	0.516	0.517	0.544
9	0.45	0.77	1.743	1.740	1.752	1.756	1.749	1.753	1.756	1.744	1.752	1.745	1.725
10	0.6	0.77	4.633	4.635	4.611	4.622	4.626	4.610	4.618	4.623	4.631	4.620	4.872
11	0.75	0.77	14.053	13.878	13.969	14.021	13.931	13.973	13.964	14.086	14.022	14.071	15.058
12	0.9	0.77	75.583	72.987	74.934	74.890	75.208	73.830	74.326	74.391	74.916	74.969	68.773
13	0.15	1	0.096	0.096	0.097	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.104
14	0.3	1	0.514	0.517	0.516	0.518	0.520	0.518	0.516	0.516	0.517	0.518	0.544
15	0.45	1	1.756	1.762	1.753	1.762	1.751	1.755	1.758	1.762	1.754	1.752	1.725
16	0.6	1	4.676	4.650	4.627	4.650	4.644	4.642	4.634	4.646	4.633	4.656	4.872
17	0.75	1	14.439	14.600	14.475	14.592	14.572	14.487	14.458	14.625	14.649	14.659	15.058
18	0.9	1	87.467	88.179	85.933	85.616	86.800	85.757	82.813	88.430	87.599	86.612	68.773
19	0.15	1.23	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.097	0.097	0.104
20	0.3	1.23	0.520	0.519	0.517	0.517	0.521	0.519	0.519	0.511	0.523	0.520	0.544
21	0.45	1.23	1.771	1.759	1.761	1.767	1.760	1.766	1.758	1.757	1.766	1.761	1.725
22	0.6	1.23	4.740	4.762	4.704	4.724	4.690	4.662	4.679	4.794	4.762	4.693	4.872
23	0.75	1.23	15.157	15.224	15.294	15.116	14.964	15.089	15.316	15.282	15.187	15.126	15.058
24	0.9	1.23	97.470	96.299	95.890	94.038	98.563	93.438	98.442	94.355	99.468	97.255	68.773
25	0.15	1.5	0.097	0.096	0.096	0.096	0.096	0.097	0.096	0.096	0.097	0.097	0.104
26	0.3	1.5	0.523	0.521	0.524	0.521	0.521	0.522	0.521	0.520	0.525	0.521	0.544
27	0.45	1.5	1.783	1.776	1.767	1.776	1.766	1.773	1.774	1.775	1.772	1.775	1.725
28	0.6	1.5	4.947	4.921	4.948	4.878	4.921	4.950	4.950	4.947	4.909	4.928	4.872
29	0.75	1.5	16.159	15.686	15.980	16.089	15.950	15.792	15.835	15.966	15.875	16.023	15.058
30	0.9	1.5	108.275	107.093	108.557	108.392	111.542	109.732	112.363	114.658	112.511	109.357	68.773

APPENDIX D: ABSOLUTE RELATIVE ERROR FOR WIP AT INPUT STATIONS TESTING

For Layout X

		For Layout X Total WIP at Input Stations From									
		Absolute relative error for Rep									
Rho	SCV	1	2	3	4	5	6	7	8	9	10
0.15	0.5	2.04%	0.06%	0.06%	0.98%	3.13%	2.04%	4.24%	2.04%	2.04%	0.06%
0.3	0.5	6.98%	7.20%	6.98%	6.98%	6.75%	7.66%	7.66%	6.75%	7.43%	6.98%
0.45	0.5	8.41%	9.29%	7.97%	9.00%	8.85%	9.22%	8.26%	7.03%	7.97%	8.26%
0.6	0.5	13.44%	12.53%	13.47%	12.42%	13.19%	13.56%	12.65%	13.39%	12.93%	12.45%
0.75	0.5	20.31%	20.54%	20.44%	19.71%	19.55%	20.37%	21.13%	19.83%	19.87%	19.55%
0.9	0.5	12.68%	13.43%	12.43%	10.46%	10.32%	14.01%	11.70%	11.71%	15.24%	10.92%
0.15	0.77	2.04%	0.98%	0.06%	0.98%	0.98%	2.04%	2.04%	0.98%	0.06%	0.06%
0.3	0.77	5.20%	5.20%	5.64%	5.64%	5.86%	6.30%	5.64%	6.30%	6.98%	5.86%
0.45	0.77	5.20%	5.13%	5.00%	5.20%	5.83%	5.00%	5.20%	5.55%	5.55%	5.27%
0.6	0.77	6.08%	6.56%	6.92%	6.67%	7.00%	6.67%	6.92%	7.02%	6.84%	7.20%
0.75	0.77	6.56%	7.41%	7.15%	6.80%	7.33%	6.84%	6.63%	6.41%	6.32%	7.82%
0.9	0.77	13.74%	12.88%	14.46%	15.76%	12.47%	15.31%	15.80%	13.85%	11.95%	13.65%
0.15	1	0.98%	0.98%	3.13%	1.08%	2.04%	2.04%	0.98%	0.06%	1.08%	0.06%
0.3	1	5.42%	5.64%	5.42%	4.98%	5.20%	4.98%	5.86%	5.42%	5.64%	4.55%
0.45	1	2.71%	3.24%	2.58%	2.45%	2.12%	2.45%	2.51%	3.04%	2.97%	2.58%
0.6	1	1.22%	1.89%	1.10%	2.35%	1.47%	1.36%	1.68%	1.17%	1.29%	1.45%
0.75	1	2.84%	1.88%	2.75%	3.09%	1.59%	2.79%	2.56%	2.08%	3.27%	2.25%
0.9	1	29.86%	27.83%	29.20%	27.12%	30.84%	27.49%	26.71%	29.76%	29.04%	29.75%
0.15	1.23	0.98%	0.06%	0.06%	0.06%	4.02%	1.08%	3.06%	1.08%	2.08%	0.06%
0.3	1.23	5.20%	3.70%	4.12%	4.34%	3.70%	4.12%	4.77%	3.70%	4.34%	4.12%
0.45	1.23	0.54%	0.45%	0.36%	0.54%	0.30%	0.64%	0.33%	0.05%	0.97%	1.52%
0.6	1.23	2.55%	2.27%	2.74%	1.97%	3.12%	3.16%	3.47%	3.39%	3.07%	3.47%
0.75	1.23	10.36%	9.26%	10.63%	10.22%	10.36%	10.85%	10.80%	10.57%	10.03%	9.30%
0.9	1.23	38.41%	38.26%	42.42%	37.96%	37.25%	38.77%	40.20%	39.45%	38.02%	39.17%
0.15	1.5	2.08%	2.08%	2.08%	4.02%	1.08%	3.06%	3.06%	1.08%	4.02%	1.08%
0.3	1.5	2.85%	3.06%	2.65%	2.44%	3.48%	2.85%	2.23%	2.23%	3.27%	3.27%
0.45	1.5	5.47%	4.00%	5.42%	5.64%	4.63%	4.00%	5.69%	4.57%	4.00%	5.30%
0.6	1.5	8.57%	7.88%	7.76%	8.33%	7.63%	7.44%	7.99%	7.97%	8.48%	8.25%
0.75	1.5	18.90%	17.21%	18.26%	17.73%	17.95%	18.59%	17.42%	18.84%	18.31%	18.34%
0.9	1.5	48.67%	45.27%	45.89%	48.02%	47.29%	47.36%	47.76%	47.50%	46.99%	48.84%

For Layout Y

		For Layout Y Total WIP at Input Stations From									
		Absolute relative error for Rep									
Rho	SCV	1	2	3	4	5	6	7	8	9	10
0.15	0.5	1.44%	1.44%	1.44%	2.48%	3.54%	0.43%	2.48%	0.43%	2.48%	3.54%
0.3	0.5	7.02%	7.24%	6.80%	7.68%	7.24%	6.58%	6.37%	6.58%	6.80%	7.24%
0.45	0.5	8.96%	9.03%	8.67%	8.82%	9.03%	8.96%	8.96%	8.89%	8.60%	8.82%
0.6	0.5	13.65%	13.90%	12.82%	13.57%	13.15%	13.48%	13.51%	13.18%	12.71%	13.40%
0.75	0.5	17.97%	18.81%	17.60%	17.96%	18.08%	18.57%	18.21%	17.99%	17.50%	17.59%
0.9	0.5	4.22%	3.07%	3.88%	5.99%	5.27%	3.25%	3.59%	3.61%	4.72%	4.43%
0.15	0.77	0.43%	1.44%	1.44%	2.48%	3.54%	0.56%	1.44%	0.56%	0.43%	1.44%
0.3	0.77	5.72%	7.02%	6.15%	5.94%	6.37%	6.15%	6.37%	5.72%	6.15%	5.51%
0.45	0.77	3.18%	3.18%	4.09%	4.35%	4.55%	5.01%	3.76%	4.09%	3.37%	4.09%
0.6	0.77	5.79%	5.84%	5.28%	5.84%	6.50%	6.62%	5.84%	5.82%	5.69%	5.31%
0.75	0.77	5.12%	4.59%	4.34%	4.61%	4.15%	4.54%	3.48%	3.97%	4.18%	5.66%
0.9	0.77	21.84%	18.51%	20.62%	21.55%	18.92%	18.90%	21.18%	19.34%	21.45%	19.30%
0.15	1	0.56%	0.56%	0.43%	0.43%	0.43%	2.48%	1.54%	0.56%	0.43%	1.44%
0.3	1	4.67%	4.88%	4.25%	4.46%	4.88%	4.67%	4.46%	4.46%	4.67%	4.46%
0.45	1	1.16%	1.03%	0.66%	0.79%	1.72%	1.47%	0.18%	0.91%	0.79%	1.41%
0.6	1	0.11%	0.41%	0.26%	0.17%	0.24%	0.52%	0.45%	0.82%	0.71%	0.06%
0.75	1	5.33%	6.07%	4.96%	4.60%	5.20%	5.84%	6.21%	5.36%	5.04%	5.11%
0.9	1	34.73%	33.28%	33.61%	32.59%	35.18%	35.33%	34.46%	34.12%	33.79%	31.55%
0.15	1.23	0.56%	0.43%	0.43%	1.54%	1.54%	0.43%	0.56%	0.56%	0.43%	1.44%
0.3	1.23	3.23%	3.63%	3.84%	4.04%	3.63%	3.23%	3.63%	3.02%	3.43%	3.02%
0.45	1.23	2.94%	3.68%	1.20%	1.26%	1.85%	3.23%	3.06%	2.77%	3.34%	3.73%
0.6	1.23	5.83%	4.93%	5.60%	5.31%	5.21%	4.78%	4.58%	4.72%	5.11%	5.40%
0.75	1.23	14.09%	12.70%	14.14%	13.44%	13.01%	13.33%	13.02%	13.60%	13.69%	13.95%
0.9	1.23	43.89%	42.93%	43.59%	43.31%	43.82%	42.61%	41.92%	45.76%	43.82%	43.02%
0.15	1.5	1.54%	0.43%	0.56%	0.56%	1.54%	0.43%	0.43%	1.54%	0.56%	0.56%
0.3	1.5	0.31%	0.12%	0.50%	2.02%	0.12%	0.50%	0.87%	0.07%	0.50%	0.50%
0.45	1.5	6.98%	6.46%	6.51%	6.24%	6.93%	5.66%	6.30%	6.93%	7.19%	6.77%
0.6	1.5	10.71%	10.29%	11.38%	10.64%	10.60%	11.03%	10.81%	10.83%	11.51%	10.60%
0.75	1.5	21.84%	21.21%	21.63%	20.84%	21.13%	21.46%	20.90%	21.23%	21.50%	21.89%
0.9	1.5	52.58%	50.43%	51.09%	50.39%	51.63%	50.31%	50.11%	51.11%	52.04%	51.44%

For Layout Z

		For Layout Z Total WIP at Input Stations From									
		Absolute relative error									
Rho	SCV	1	2	3	4	5	6	7	8	9	10
0.15	0.5	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%
0.3	0.5	5.96%	5.96%	5.35%	6.17%	5.96%	6.38%	6.17%	6.17%	6.17%	5.35%
0.45	0.5	1.28%	1.40%	1.06%	1.11%	1.40%	1.51%	1.34%	1.51%	1.62%	1.40%
0.6	0.5	6.25%	5.67%	5.69%	6.13%	6.13%	6.29%	5.83%	5.60%	5.97%	5.85%
0.75	0.5	12.76%	13.47%	12.29%	12.14%	13.16%	13.47%	13.02%	12.48%	11.72%	12.59%
0.9	0.5	10.69%	12.85%	12.69%	10.10%	10.75%	12.46%	13.16%	12.06%	9.68%	9.60%
0.15	0.77	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%
0.3	0.77	5.55%	5.96%	5.96%	4.74%	5.35%	5.14%	6.38%	6.59%	5.35%	5.14%
0.45	0.77	1.06%	0.89%	1.57%	1.79%	1.40%	1.62%	1.79%	1.11%	1.57%	1.17%
0.6	0.77	5.17%	5.12%	5.67%	5.42%	5.33%	5.69%	5.51%	5.40%	5.21%	5.47%
0.75	0.77	7.15%	8.51%	7.80%	7.40%	8.09%	7.77%	7.84%	6.90%	7.39%	7.02%
0.9	0.77	9.01%	5.77%	8.22%	8.17%	8.56%	6.85%	7.47%	7.55%	8.20%	8.26%
0.15	1	8.05%	8.05%	6.94%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%
0.3	1	5.76%	5.14%	5.35%	4.94%	4.54%	4.94%	5.35%	5.35%	5.14%	4.94%
0.45	1	1.79%	2.12%	1.62%	2.12%	1.51%	1.73%	1.90%	2.12%	1.68%	1.57%
0.6	1	4.20%	4.78%	5.31%	4.78%	4.92%	4.97%	5.15%	4.87%	5.17%	4.65%
0.75	1	4.29%	3.14%	4.03%	3.20%	3.34%	3.94%	4.15%	2.96%	2.79%	2.72%
0.9	1	21.37%	22.01%	19.97%	19.67%	20.77%	19.80%	16.95%	22.23%	21.49%	20.60%
0.15	1.23	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	8.05%	6.94%	6.94%
0.3	1.23	4.54%	4.74%	5.14%	5.14%	4.34%	4.74%	4.74%	6.38%	3.94%	4.54%
0.45	1.23	2.62%	1.96%	2.07%	2.40%	2.01%	2.35%	1.90%	1.85%	2.35%	2.07%
0.6	1.23	2.80%	2.32%	3.58%	3.14%	3.89%	4.51%	4.14%	1.64%	2.32%	3.82%
0.75	1.23	0.65%	1.09%	1.54%	0.38%	0.63%	0.20%	1.68%	1.46%	0.85%	0.45%
0.9	1.23	29.44%	28.58%	28.28%	26.87%	30.22%	26.40%	30.14%	27.11%	30.86%	29.29%
0.15	1.5	6.94%	8.05%	8.05%	8.05%	8.05%	6.94%	8.05%	8.05%	6.94%	6.94%
0.3	1.5	3.94%	4.34%	3.74%	4.34%	4.34%	4.14%	4.34%	4.54%	3.54%	4.34%
0.45	1.5	3.28%	2.90%	2.40%	2.90%	2.35%	2.73%	2.79%	2.84%	2.68%	2.84%
0.6	1.5	1.51%	0.99%	1.53%	0.11%	0.99%	1.57%	1.57%	1.51%	0.74%	1.13%
0.75	1.5	6.81%	4.00%	5.77%	6.41%	5.59%	4.65%	4.90%	5.68%	5.14%	6.02%
0.9	1.5	36.48%	35.78%	36.65%	36.55%	38.34%	37.33%	38.79%	40.02%	38.87%	37.11%

APPENDIX E: AVERAGE ERROR FOR WIP AT INPUT STATIONS TESTING

Rho	SCV	Average Error		
		Layout X	Layout Y	Layout Z
0.15	0.5	-1.62%	-1.96%	-8.05%
0.3	0.5	-7.14%	-6.95%	-5.96%
0.45	0.5	-8.42%	-8.87%	1.36%
0.6	0.5	-13.00%	-13.34%	-5.94%
0.75	0.5	-20.13%	-18.03%	-12.71%
0.9	0.5	-12.27%	-4.20%	-11.39%
0.15	0.77	-0.98%	-1.14%	-8.05%
0.3	0.77	-5.86%	-6.11%	-5.61%
0.45	0.77	-5.29%	-3.96%	1.40%
0.6	0.77	-6.79%	-5.85%	-5.40%
0.75	0.77	-6.92%	-4.46%	-7.58%
0.9	0.77	14.01%	20.18%	7.81%
0.15	1	-0.77%	-0.23%	-7.94%
0.3	1	-5.31%	-4.58%	-5.14%
0.45	1	-2.66%	-1.01%	1.82%
0.6	1	-1.50%	0.17%	-4.88%
0.75	1	2.51%	5.37%	-3.45%
0.9	1	28.78%	33.88%	20.51%
0.15	1.23	1.08%	0.17%	-7.83%
0.3	1.23	-4.21%	-3.47%	-4.82%
0.45	1.23	0.29%	2.71%	2.16%
0.6	1.23	2.92%	5.15%	-3.21%
0.75	1.23	10.24%	13.50%	0.77%
0.9	1.23	39.02%	43.48%	28.75%
0.15	1.5	2.38%	0.56%	-7.60%
0.3	1.5	-2.83%	0.14%	-4.16%
0.45	1.5	4.88%	6.60%	2.77%
0.6	1.5	8.03%	10.84%	1.16%
0.75	1.5	18.16%	21.36%	5.50%
0.9	1.5	47.38%	51.13%	37.62%

APPENDIX F: GLM PROCEDURE SAS OUTPUT FOR WIP AT INPUT STATIONS – LAYOUT X

The SAS System
1

The GLM Procedure

Class Level Information

Class	Levels	Values
Rho	5	0.15 0.3 0.45 0.6 0.75
scv_arrivals	5	0.5 0.77 1 1.23 1.5
M	2	0 1
SCV_M	10	1 2 3 4 5 6 7 8 9 10
Rho_M	10	1 2 3 4 5 6 7 8 9 10

Number of observations 500

The SAS System
2

The GLM Procedure

Dependent Variable: WIP_welch

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	12761.01653	750.64803	2931.49	<.0001
Error	482	123.42259	0.25606		
Corrected Total	499	12884.43912			

R-Square	Coeff Var	Root MSE	WIP_welch Mean
0.990421	12.46586	0.506027	4.059303

Source	DF	Type I SS	Mean Square	F Value	Pr > F
Rho	4	12708.34330	3177.08583	12407.4	<.0001
scv_arrivals	4	24.73230	6.18308	24.15	<.0001
M	1	0.25341	0.25341	0.99	0.3203
SCV_M	4	24.73230	6.18308	24.15	<.0001
Rho_M	4	2.95521	0.73880	2.89	0.0221

Source	DF	Type III SS	Mean Square	F Value	Pr > F

```
    Rho              0    0.00000000     .         .     .
    scv_arrivals          0    0.00000000     .         .     .
    M               0    0.00000000     .         .     .
    SCV_M             4    24.73230193    6.18307548    24.15   <.0001
    Rho_M             4    2.95521263    0.73880316     2.89   0.0221

                      The SAS System
3

                     The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.256063
              Critical Value of Studentized Range 3.87233
              Minimum Significant Difference     0.196


           Means with the same letter are not significantly different.


           Tukey Grouping     Mean    N  Rho

                  A    13.67246   100   0.75

                  B     4.44593   100   0.6

                  C     1.58627   100   0.45

                  D     0.49489   100   0.3

                  E     0.09696   100   0.15
                      The SAS System
4

                     The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.256063
              Critical Value of Studentized Range 3.87233
```

```
              Minimum Significant Difference     0.196


          Means with the same letter are not significantly different.


                              scv_
           Tukey Grouping     Mean   N  arrivals

                  A    4.38247  100  1.5
                  A
               B  A    4.20281  100  1.23
               B
               B  C    4.05821  100  1
                  C
               D  C    3.90995  100  0.77
               D
               D      3.74310  100  0.5

                      The SAS System
5

                     The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.256063
              Critical Value of Studentized Range 2.77879
              Minimum Significant Difference    0.0889


          Means with the same letter are not significantly different.


            Tukey Grouping     Mean   N  M

                  A    4.08182  250  1
                  A
                  A    4.03679  250  0

                      The SAS System
6

                     The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
```

```
                   II error rate than REGWQ.


              Alpha                  0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.256063
              Critical Value of Studentized Range 4.49526
              Minimum Significant Difference    0.3217


           Means with the same letter are not significantly different.


            Tukey Grouping     Mean   N  SCV_M

                   A    4.7281   50  9

                   B    4.3688   50  7
                   B
                C  B    4.0796   50  5
                C
                C       4.0368   50  2
                C
                C       4.0368   50  4
                C
                C       4.0368   50  6
                C
                C       4.0368   50  8
                C
                C       4.0368   50  10
                C
                C       3.7831   50  3

                   D    3.4494   50  1

                      The SAS System
7

                     The GLM Procedure

             Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                  0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.256063
              Critical Value of Studentized Range 4.49526
              Minimum Significant Difference    0.3217


          Means with the same letter are not significantly different.
```

Tukey Grouping	Mean	N	Rho_M
A	13.8472	50	9
B	13.4977	50	10
C	4.4799	50	8
C			
C	4.4119	50	7
D	1.6022	50	6
D			
D	1.5703	50	5
E	0.5071	50	4
E			
E	0.4827	50	3
F	0.0970	50	1
F			
F	0.0969	50	2

The SAS System

8

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	482
Error Mean Square	0.256063

Number of Means	2	3	4	5
Critical Range	0.1666212	0.1820104	0.1844935	0.1959504

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	Rho
A	13.67246	100	0.75
B	4.44593	100	0.6
C	1.58627	100	0.45
D	0.49489	100	0.3
E	0.09696	100	0.15

```
                      The SAS System
9

                     The GLM Procedure

          Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

          NOTE: This test controls the Type I experimentwise error rate.


                 Alpha            0.05
                 Error Degrees of Freedom   482
                 Error Mean Square    0.256063


      Number of Means       2       3       4       5
      Critical Range    0.1666212   0.1820104   0.1844935   0.1959504


          Means with the same letter are not significantly different.


                            scv_
           REGWQ Grouping     Mean   N  arrivals

                  A    4.38247  100  1.5

                  B    4.20281  100  1.23
                  B
               C  B    4.05821  100  1
               C
               C      3.90995  100  0.77

                  D    3.74310  100  0.5

                      The SAS System
10

                     The GLM Procedure

          Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

          NOTE: This test controls the Type I experimentwise error rate.


                 Alpha            0.05
                 Error Degrees of Freedom   482
                 Error Mean Square    0.256063


                  Number of Means       2
                  Critical Range    0.0889322


          Means with the same letter are not significantly different.
```

REGWQ Grouping	Mean	N	M
A	4.08182	250	1
A			
A	4.03679	250	0

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	482
Error Mean Square	0.256063

Number of Means	2	3	4	5	6
Critical Range	0.2610246	0.2820158	0.2935061	0.3013052	0.3071517

Number of Means	7	8	9	10
Critical Range	0.3117962	0.3156297	0.3156297	0.3216947

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	SCV_M
A	4.7281	50	9
B	4.3688	50	7
C	4.0796	50	5
C			
C	4.0368	50	2
C			
C	4.0368	50	4
C			
C	4.0368	50	6
C			
C	4.0368	50	8
C			
C	4.0368	50	10
C			
C	3.7831	50	3
D	3.4494	50	1

12

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	482
Error Mean Square	0.256063

Number of Means	2	3	4	5	6
Critical Range	0.2610246	0.2820158	0.2935061	0.3013052	0.3071517

Number of Means	7	8	9	10
Critical Range	0.3117962	0.3156297	0.3156297	0.3216947

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	Rho_M
A	13.8472	50	9
B	13.4977	50	10
C	4.4799	50	8
C			
C	4.4119	50	7
D	1.6022	50	6
D			
D	1.5703	50	5
E	0.5071	50	4
E			
E	0.4827	50	3
F	0.0970	50	1
F			
F	0.0969	50	2

APPENDIX G: GLM PROCEDURE SAS OUTPUT FOR WIP AT INPUT STATIONS – LAYOUT Y

```
                      The SAS System
1

                     The GLM Procedure

                   Class Level Information

            Class        Levels  Values

            Rho           5  0.15 0.3 0.45 0.6 0.75

            scv_arrivals       5  0.5 0.77 1 1.23 1.5

            M            2  0 1

            SCV_M          10  1 2 3 4 5 6 7 8 9 10

            Rho_M          10  1 2 3 4 5 6 7 8 9 10


                  Number of observations  500

                      The SAS System
2

                     The GLM Procedure

Dependent Variable: WIP_welch

                        Sum of
    Source            DF      Squares   Mean Square  F Value  Pr > F

    Model             17   13732.30122    807.78242  2549.77  <.0001

    Error            482    152.70022     0.31681

    Corrected Total      499   13885.00143


            R-Square   Coeff Var   Root MSE  WIP_welch Mean

            0.989003   13.37538   0.562855     4.208140


    Source            DF    Type I SS   Mean Square  F Value  Pr > F

    Rho              4   13652.72593   3413.18148  10773.7  <.0001
    scv_arrivals          4    31.85144     7.96286   25.13  <.0001
    M              1     2.95744     2.95744    9.34  0.0024
    SCV_M             4    31.85144     7.96286   25.13  <.0001
    Rho_M             4    12.91498     3.22874   10.19  <.0001


    Source            DF   Type III SS   Mean Square  F Value  Pr > F
```

```
    Rho              0   0.00000000    .        .    .
    scv_arrivals         0   0.00000000    .        .    .
    M              0   0.00000000    .        .    .
    SCV_M            4   31.85143673   7.96285918   25.13  <.0001
    Rho_M            4   12.91497950   3.22874487   10.19  <.0001

                      The SAS System
3

                     The GLM Procedure

             Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.316805
              Critical Value of Studentized Range 3.87233
              Minimum Significant Difference     0.218


           Means with the same letter are not significantly different.


           Tukey Grouping     Mean   N  Rho

                  A   14.17263  100  0.75

                  B    4.60615  100  0.6

                  C    1.64777  100  0.45

                  D    0.51397  100  0.3

                  E    0.10017  100  0.15
                      The SAS System
4

                     The GLM Procedure

             Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.316805
              Critical Value of Studentized Range 3.87233
```

```
              Minimum Significant Difference     0.218


          Means with the same letter are not significantly different.


                                 scv_
           Tukey Grouping     Mean   N  arrivals

                  A    4.57326  100  1.5
                  A
               B  A    4.37407  100  1.23
               B
               B  C    4.20628  100  1
                  C
               D  C    4.03751  100  0.77
               D
               D     3.84960  100  0.5

                      The SAS System
5

                     The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.316805
              Critical Value of Studentized Range 2.77879
              Minimum Significant Difference    0.0989


          Means with the same letter are not significantly different.


            Tukey Grouping     Mean   N  M

                  A    4.28505  250  1

                  B    4.13123  250  0

                      The SAS System
6

                     The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
```

```
                  II error rate than REGWQ.


             Alpha                   0.05
             Error Degrees of Freedom         482
             Error Mean Square          0.316805
             Critical Value of Studentized Range 4.49526
             Minimum Significant Difference    0.3578


          Means with the same letter are not significantly different.


           Tukey Grouping     Mean   N  SCV_M

                  A    5.0153   50  9

                  B    4.6169   50  7
                  B
               C  B    4.2813   50  5
               C
               C       4.1312   50  2
               C
               C       4.1312   50  4
               C
               C       4.1312   50  6
               C
               C       4.1312   50  8
               C
               C       4.1312   50  10
               C
               C       3.9438   50  3

                  D    3.5680   50  1

                     The SAS System
7

                    The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                  II error rate than REGWQ.


             Alpha                   0.05
             Error Degrees of Freedom         482
             Error Mean Square          0.316805
             Critical Value of Studentized Range 4.49526
             Minimum Significant Difference    0.3578


          Means with the same letter are not significantly different.
```

```
     Tukey Grouping     Mean   N  Rho_M

           A    14.5709   50  9

           B    13.7744   50  10

           C    4.6083   50  7
           C
           C    4.6040   50  8

           D    1.6529   50  6
           D
           D    1.6426   50  5

           E    0.5244   50  4
           E
           E    0.5036   50  3

           F    0.1004   50  2
           F
           F    0.0999   50  1

                The SAS System
8

                 The GLM Procedure

     Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

     NOTE: This test controls the Type I experimentwise error rate.


           Alpha            0.05
           Error Degrees of Freedom   482
           Error Mean Square    0.316805


 Number of Means       2       3       4       5
 Critical Range    0.185333   0.2024504   0.2052124   0.2179559


     Means with the same letter are not significantly different.


     REGWQ Grouping     Mean   N  Rho

            A   14.17263  100  0.75

            B    4.60615  100  0.6

            C    1.64777  100  0.45

            D    0.51397  100  0.3

            E    0.10017  100  0.15
```

```
                      The SAS System
9

                     The GLM Procedure

          Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

          NOTE: This test controls the Type I experimentwise error rate.


                 Alpha            0.05
                 Error Degrees of Freedom   482
                 Error Mean Square    0.316805


      Number of Means       2       3       4       5
      Critical Range    0.185333   0.2024504   0.2052124   0.2179559


          Means with the same letter are not significantly different.


                           scv_
           REGWQ Grouping     Mean   N  arrivals

                  A    4.57326  100  1.5

                  B    4.37407  100  1.23
                  B
               C  B    4.20628  100  1
               C
               C      4.03751  100  0.77

                  D    3.84960  100  0.5

                      The SAS System
10

                     The GLM Procedure

          Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

          NOTE: This test controls the Type I experimentwise error rate.


                 Alpha            0.05
                 Error Degrees of Freedom   482
                 Error Mean Square    0.316805


                  Number of Means       2
                  Critical Range    0.0989194


          Means with the same letter are not significantly different.
```

REGWQ Grouping	Mean	N	M
A	4.28505	250	1
B	4.13123	250	0

The SAS System

11

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	482
Error Mean Square	0.316805

Number of Means	2	3	4	5	6
Critical Range	0.290338	0.3136866	0.3264672	0.3351422	0.3416452

Number of Means	7	8	9	10
Critical Range	0.3468114	0.3510754	0.3510754	0.3578214

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	SCV_M
A	5.0153	50	9
B	4.6169	50	7
C	4.2813	50	5
C			
C	4.1312	50	2
C			
C	4.1312	50	4
C			
C	4.1312	50	6
C			
C	4.1312	50	8
C			
C	4.1312	50	10
C			
C	3.9438	50	3
D	3.5680	50	1

The SAS System

12

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	482
Error Mean Square	0.316805

Number of Means	2	3	4	5	6
Critical Range	0.290338	0.3136866	0.3264672	0.3351422	0.3416452

Number of Means	7	8	9	10
Critical Range	0.3468114	0.3510754	0.3510754	0.3578214

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	Rho_M
A	14.5709	50	9
B	13.7744	50	10
C	4.6083	50	7
C			
C	4.6040	50	8
D	1.6529	50	6
D			
D	1.6426	50	5
E	0.5244	50	4
E			
E	0.5036	50	3
F	0.1004	50	2
F			
F	0.0999	50	1

APPENDIX H: GLM PROCEDURE SAS OUTPUT FOR WIP AT INPUT STATIONS – LAYOUT Z

```
                      The SAS System
1

                     The GLM Procedure

                   Class Level Information

            Class       Levels  Values

            Rho           5  0.15 0.3 0.45 0.6 0.75

            scv_arrivals      5  0.5 0.77 1 1.23 1.5

            M           2  0 1

            SCV_M         10  1 2 3 4 5 6 7 8 9 10

            Rho_M         10  1 2 3 4 5 6 7 8 9 10


                  Number of observations  500

                      The SAS System
2

                     The GLM Procedure

Dependent Variable: WIP_welch

                        Sum of
    Source           DF     Squares   Mean Square  F Value  Pr > F

    Model            17   14966.51846    880.38344  13711.7  <.0001

    Error           482    30.94774     0.06421

    Corrected Total      499   14997.46619


            R-Square   Coeff Var   Root MSE  WIP_welch Mean

            0.997936   5.761172   0.253391     4.398252


    Source           DF    Type I SS   Mean Square  F Value  Pr > F

    Rho             4   14950.21507   3737.55377  58211.1  <.0001
    scv_arrivals         4     5.20085     1.30021   20.25  <.0001
    M             1     1.94040     1.94040   30.22  <.0001
    SCV_M           4     5.20085     1.30021   20.25  <.0001
    Rho_M           4     3.96128     0.99032   15.42  <.0001


    Source           DF   Type III SS   Mean Square  F Value  Pr > F
```

```
    Rho              0   0.00000000    .        .    .
    scv_arrivals         0   0.00000000    .        .    .
    M              0   0.00000000    .        .    .
    SCV_M            4   5.20085293   1.30021323   20.25  <.0001
    Rho_M            4   3.96127836   0.99031959   15.42  <.0001

                      The SAS System
3

                     The GLM Procedure

             Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.064207
              Critical Value of Studentized Range 3.87233
              Minimum Significant Difference    0.0981


           Means with the same letter are not significantly different.


           Tukey Grouping     Mean   N  Rho

                  A   14.83158  100  0.75

                  B    4.78812  100  0.6

                  C    1.74131  100  0.45

                  D    0.53031  100  0.3

                  E    0.09993  100  0.15
                      The SAS System
4

                     The GLM Procedure

             Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom         482
              Error Mean Square          0.064207
              Critical Value of Studentized Range 3.87233
```

```
             Minimum Significant Difference    0.0981


         Means with the same letter are not significantly different.


                              scv_
          Tukey Grouping     Mean   N  arrivals

                 A    4.55601  100  1.5

                 B    4.45766  100  1.23
                 B
              C  B    4.38737  100  1
              C
              C  D    4.32821  100  0.77
                 D
                 D    4.26199  100  0.5

                     The SAS System
5

                    The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


             Alpha                   0.05
             Error Degrees of Freedom         482
             Error Mean Square          0.064207
             Critical Value of Studentized Range 2.77879
             Minimum Significant Difference    0.0445


         Means with the same letter are not significantly different.


           Tukey Grouping     Mean   N  M

                 A    4.46055  250  0

                 B    4.33596  250  1

                     The SAS System
6

                    The GLM Procedure

            Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
```

```
                   II error rate than REGWQ.


              Alpha                    0.05
              Error Degrees of Freedom          482
              Error Mean Square           0.064207
              Critical Value of Studentized Range 4.49526
              Minimum Significant Difference     0.1611


           Means with the same letter are not significantly different.


            Tukey Grouping      Mean    N  SCV_M

                   A     4.65148   50  9

                   B     4.46055   50  2
                   B
                   B     4.46055   50  4
                   B
                   B     4.46055   50  6
                   B
                   B     4.46055   50  8
                   B
                   B     4.46055   50  10
                   B
                   B     4.45478   50  7
                   B
                C  B     4.31420   50  5
                C
                C  D     4.19588   50  3
                   D
                   D     4.06344   50  1

                      The SAS System
7

                     The GLM Procedure

             Tukey's Studentized Range (HSD) Test for WIP_welch

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                    0.05
              Error Degrees of Freedom          482
              Error Mean Square           0.064207
              Critical Value of Studentized Range 4.49526
              Minimum Significant Difference     0.1611


          Means with the same letter are not significantly different.
```

```
        Tukey Grouping     Mean   N  Rho_M

              A   15.05836   50  10

              B   14.60480   50  9

              C    4.87249   50  8

              D    4.70376   50  7

              E    1.75804   50  5
              E
              E    1.72458   50  6

              F    0.54359   50  4
              F
              F    0.51704   50  3

              G    0.10373   50  2
              G
              G    0.09614   50  1

                   The SAS System
8

                  The GLM Procedure

       Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

       NOTE: This test controls the Type I experimentwise error rate.


              Alpha            0.05
              Error Degrees of Freedom   482
              Error Mean Square    0.064207


    Number of Means       2       3       4       5
    Critical Range    0.0834348   0.0911409   0.0923843   0.0981213


        Means with the same letter are not significantly different.


        REGWQ Grouping     Mean   N  Rho

               A   14.83158  100  0.75

               B    4.78812  100  0.6

               C    1.74131  100  0.45

               D    0.53031  100  0.3

               E    0.09993  100  0.15
```

The SAS System

9

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	482
Error Mean Square	0.064207

Number of Means	2	3	4	5
Critical Range	0.0834348	0.0911409	0.0923843	0.0981213

Means with the same letter are not significantly different.

REGWQ Grouping		Mean	N	scv_ arrivals
	A	4.55601	100	1.5
	B	4.45766	100	1.23
	B			
C	B	4.38737	100	1
C				
C	D	4.32821	100	0.77
	D			
	D	4.26199	100	0.5

The SAS System

10

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	482
Error Mean Square	0.064207

Number of Means	2
Critical Range	0.0445324

Means with the same letter are not significantly different.

```
            REGWQ Grouping     Mean    N  M

                  A    4.46055  250  0

                  B    4.33596  250  1

                      The SAS System
11

                     The GLM Procedure

          Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

          NOTE: This test controls the Type I experimentwise error rate.


                 Alpha             0.05
                 Error Degrees of Freedom   482
                 Error Mean Square    0.064207


   Number of Means       2         3         4         5         6
   Critical Range    0.1307069   0.1412182   0.1469719   0.1508772   0.1538048

      Number of Means       7         8         9        10
      Critical Range    0.1561306   0.1580502   0.1580502   0.1610872


           Means with the same letter are not significantly different.


            REGWQ Grouping     Mean    N  SCV_M

                   A    4.65148   50  9

                   B    4.46055   50  2
                   B
                   B    4.46055   50  4
                   B
                   B    4.46055   50  6
                   B
                   B    4.46055   50  8
                   B
                   B    4.46055   50  10
                   B
                   B    4.45478   50  7
                   B
                C  B    4.31420   50  5
                C
                C     4.19588   50  3

                   D    4.06344   50  1

                      The SAS System
```

12

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP_welch

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	482
Error Mean Square	0.064207

Number of Means	2	3	4	5	6
Critical Range	0.1307069	0.1412182	0.1469719	0.1508772	0.1538048

Number of Means	7	8	9	10
Critical Range	0.1561306	0.1580502	0.1580502	0.1610872

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	Rho_M
A	15.05836	50	10
B	14.60480	50	9
C	4.87249	50	8
D	4.70376	50	7
E	1.75804	50	5
E			
E	1.72458	50	6
F	0.54359	50	4
F			
F	0.51704	50	3
G	0.10373	50	2
G			
G	0.09614	50	1

APPENDIX I: WIP FROM THE LLDP TESTING

							WIP from Replication									
Test	Ω	ρ_{LCMHS}	t	θ	S	θS	1	2	3	4	5	6	7	8	9	10
1	0.10	0.15	0	1	1	1	32.78	31.26	31.44	33.94	31.32	32.64	31.06	32.56	31.83	31.51
2	0.10	0.15	0	1	2	2	88.57	84.05	88.59	84.98	85.06	84.08	88.70	84.04	85.29	90.18
3	0.10	0.15	0	2	1	3	31.29	33.72	34.47	30.58	31.86	34.82	33.80	31.26	35.06	35.28
4	0.10	0.15	0	2	2	4	85.29	84.07	85.82	85.34	84.87	84.07	86.12	85.01	85.25	88.73
5	0.10	0.15	7	1	1	1	35.48	34.61	35.36	37.94	35.02	35.28	37.24	35.32	36.83	34.77
6	0.10	0.15	7	1	2	2	90.37	87.10	87.08	87.08	87.63	88.27	87.10	88.37	88.47	90.39
7	0.10	0.15	7	2	1	3	37.33	38.30	39.29	40.52	35.32	38.10	36.38	34.81	36.39	40.21
8	0.10	0.15	7	2	2	4	91.40	88.51	88.00	92.89	87.14	87.14	90.23	94.72	92.86	87.12
9	0.10	0.15	15	1	1	1	40.81	44.30	39.90	43.37	41.68	40.29	41.40	39.70	42.75	39.13
10	0.10	0.15	15	1	2	2	92.82	94.31	96.26	92.82	94.66	91.48	92.44	95.61	92.54	91.92
11	0.10	0.15	15	2	1	3	45.10	44.61	45.12	42.72	41.93	39.81	41.23	41.55	43.44	42.80
12	0.10	0.15	15	2	2	4	92.96	91.67	91.75	94.96	93.16	93.56	93.02	91.62	92.99	98.45
13	0.10	0.50	0	1	1	1	103.60	104.27	102.72	103.64	108.96	111.47	106.19	104.41	103.04	109.68
14	0.10	0.50	0	1	2	2	285.93	306.31	290.16	281.85	309.84	280.58	296.43	284.49	280.66	293.27
15	0.10	0.50	0	2	1	3	111.49	111.48	122.27	106.22	107.93	109.05	105.70	110.95	105.16	117.95
16	0.10	0.50	0	2	2	4	283.95	306.37	280.86	296.82	291.94	309.61	285.33	291.55	288.93	280.88
17	0.10	0.50	7	1	1	1	107.77	108.58	107.85	114.90	111.46	109.37	106.80	111.05	108.20	107.82
18	0.10	0.50	7	1	2	2	293.71	284.66	306.25	308.82	283.81	289.68	284.98	300.77	305.25	288.26
19	0.10	0.50	7	2	1	3	110.37	116.66	119.45	116.02	109.89	121.24	122.51	108.01	112.32	110.91
20	0.10	0.50	7	2	2	4	284.22	283.94	283.80	283.89	292.16	283.84	283.64	289.38	306.04	299.62
21	0.10	0.50	15	1	1	1	113.50	115.87	115.11	121.11	112.88	122.32	112.20	120.47	113.56	114.20
22	0.10	0.50	15	1	2	2	292.29	306.59	288.30	288.26	288.34	292.64	308.76	303.61	288.10	292.81
23	0.10	0.50	15	2	1	3	115.37	115.67	115.79	116.34	112.69	116.14	113.23	120.59	118.41	121.66
24	0.10	0.50	15	2	2	4	288.56	288.55	299.43	292.75	297.18	292.93	291.27	289.76	300.74	288.68
25	0.10	0.85	0	1	1	1	187.18	177.82	177.46	183.33	175.06	187.32	188.44	175.20	180.61	189.73

26	0.10	0.85	0	1	2	2	479.13	514.66	487.53	479.54	485.10	486.11	506.20	496.68	486.04	493.57
27	0.10	0.85	0	2	1	3	193.16	182.96	182.31	185.07	181.86	216.65	192.65	178.42	199.18	186.69
28	0.10	0.85	0	2	2	4	510.55	509.91	506.76	499.96	480.11	498.46	485.07	484.19	479.59	487.22
29	0.10	0.85	7	1	1	1	181.12	191.18	185.03	192.27	181.12	185.42	186.75	180.15	178.80	182.12
30	0.10	0.85	7	1	2	2	521.32	482.23	505.32	518.29	482.32	489.88	529.04	509.68	482.30	534.50
31	0.10	0.85	7	2	1	3	192.50	182.55	198.26	180.73	203.17	182.25	182.61	182.38	177.26	189.08
32	0.10	0.85	7	2	2	4	514.76	516.33	500.15	533.77	492.69	488.23	508.40	485.00	528.25	482.82
33	0.10	0.85	15	1	1	1	184.54	200.26	183.63	207.96	186.51	186.72	203.90	187.65	188.08	192.33
34	0.10	0.85	15	1	2	2	491.93	491.86	508.85	487.20	487.28	504.56	489.10	504.80	496.70	519.90
35	0.10	0.85	15	2	1	3	189.98	190.47	191.59	191.86	192.19	189.50	193.88	187.32	198.03	186.39
36	0.10	0.85	15	2	2	4	513.93	487.94	487.08	505.66	503.56	523.02	504.88	491.74	492.49	490.23
37	1	0.15	0	1	1	1	36.52	33.72	35.13	34.01	38.46	36.52	34.81	35.78	37.33	37.86
38	1	0.15	0	1	2	2	84.03	85.70	89.04	87.94	91.46	88.89	89.35	88.61	84.01	85.25
39	1	0.15	0	2	1	3	41.71	42.45	43.59	43.71	39.33	41.47	38.93	40.21	40.54	45.82
40	1	0.15	0	2	2	4	88.89	84.07	90.88	86.00	88.18	84.09	85.69	85.90	84.11	84.10
41	1	0.15	7	1	1	1	42.02	36.57	42.15	40.37	41.26	41.38	39.46	40.69	40.17	43.47
42	1	0.15	7	1	2	2	88.13	90.52	87.05	87.08	90.43	92.55	88.76	88.09	91.14	88.77
43	1	0.15	7	2	1	3	46.88	47.73	43.26	45.51	41.54	46.71	48.01	42.63	42.68	46.71
44	1	0.15	7	2	2	4	88.36	88.46	89.28	87.21	87.55	90.08	92.38	88.43	92.31	87.13
45	1	0.15	15	1	1	1	45.53	47.93	43.74	44.41	43.76	44.58	44.44	44.30	45.12	44.61
46	1	0.15	15	1	2	2	92.94	96.62	95.74	95.12	99.73	96.70	94.61	92.25	95.50	94.12
47	1	0.15	15	2	1	3	50.59	47.17	52.19	48.89	49.89	45.89	49.60	46.92	50.69	48.13
48	1	0.15	15	2	2	4	91.62	92.59	92.94	92.35	93.02	91.82	92.00	93.01	91.51	95.62
49	1	0.50	0	1	1	1	113.26	106.56	103.81	104.35	106.60	105.25	113.09	115.57	112.24	107.01
50	1	0.50	0	1	2	2	280.67	290.08	281.12	280.52	280.51	286.57	286.30	295.64	280.57	286.18
51	1	0.50	0	2	1	3	113.86	119.66	121.33	111.68	120.13	128.19	120.93	135.42	111.48	126.85
52	1	0.50	0	2	2	4	280.95	280.94	283.44	286.51	291.38	282.52	300.59	280.75	283.40	308.94
53	1	0.50	7	1	1	1	110.46	110.32	109.10	112.86	107.99	108.57	110.98	124.07	108.54	109.63
54	1	0.50	7	1	2	2	286.81	289.36	283.58	283.66	283.78	285.58	307.18	287.83	283.66	306.23
55	1	0.50	7	2	1	3	126.40	116.07	122.33	120.05	122.19	126.08	116.98	115.54	115.09	120.00

56	1	0.50	7	2	2	4	300.58	287.20	283.87	285.82	283.96	289.34	283.93	287.28	299.45	284.16
57	1	0.50	15	1	1	1	114.00	124.91	115.06	116.03	113.60	115.16	110.80	114.74	114.20	112.59
58	1	0.50	15	1	2	2	296.53	288.22	289.97	314.29	296.61	292.13	288.18	303.14	297.11	291.30
59	1	0.50	15	2	1	3	126.85	133.36	137.98	121.18	122.46	121.29	128.87	120.99	126.11	123.94
60	1	0.50	15	2	2	4	298.25	301.87	291.06	307.50	300.46	315.67	288.85	288.31	292.89	288.16
61	1	0.85	0	1	1	1	183.09	179.06	177.11	178.70	174.88	180.82	179.02	181.93	176.50	179.37
62	1	0.85	0	1	2	2	509.14	489.45	479.21	503.48	479.22	486.69	479.20	484.20	484.30	482.33
63	1	0.85	0	2	1	3	205.87	203.69	184.28	173.66	191.97	202.23	212.93	198.93	192.00	195.81
64	1	0.85	0	2	2	4	505.46	489.20	496.86	493.65	498.38	495.51	513.46	515.44	527.63	484.23
65	1	0.85	7	1	1	1	180.79	183.42	183.71	192.53	182.46	196.47	182.50	181.20	181.32	181.35
66	1	0.85	7	1	2	2	482.66	482.60	482.53	494.20	509.94	487.22	508.61	505.08	482.60	489.18
67	1	0.85	7	2	1	3	205.07	186.31	187.54	186.48	215.35	190.70	198.15	205.74	185.03	194.58
68	1	0.85	7	2	2	4	521.61	482.79	500.19	482.40	514.59	483.16	484.70	496.73	485.11	503.69
69	1	0.85	15	1	1	1	187.40	186.10	200.98	182.42	199.51	186.59	191.19	182.42	187.11	193.44
70	1	0.85	15	1	2	2	507.19	519.26	486.82	486.68	532.51	492.82	497.26	493.84	487.25	508.22
71	1	0.85	15	2	1	3	193.98	202.75	208.32	207.96	187.91	206.96	208.40	213.46	202.77	201.87
72	1	0.85	15	2	2	4	494.93	529.93	514.41	487.06	508.69	487.65	487.76	556.08	494.13	501.49
73	10	0.15	0	1	1	1	56.84	58.99	59.60	59.11	59.26	61.54	58.40	58.04	57.96	62.85
74	10	0.15	0	1	2	2	85.60	84.00	88.15	88.61	89.54	84.00	83.99	88.13	86.49	84.06
75	10	0.15	0	2	1	3	69.10	73.07	76.47	70.31	58.56	68.58	72.93	84.02	69.59	74.21
76	10	0.15	0	2	2	4	84.01	89.88	84.90	87.06	90.53	85.34	86.53	84.08	85.01	91.68
77	10	0.15	7	1	1	1	62.62	60.07	60.82	59.48	62.79	60.37	60.69	62.28	61.87	63.43
78	10	0.15	7	1	2	2	87.16	91.55	87.04	87.92	87.06	93.81	98.59	87.48	93.14	87.13
79	10	0.15	7	2	1	3	78.09	72.75	61.27	77.27	72.09	75.28	73.29	59.43	64.78	76.97
80	10	0.15	7	2	2	4	92.66	89.64	87.99	87.21	87.18	90.25	87.95	91.46	88.01	92.90
81	10	0.15	15	1	1	1	65.57	64.83	67.09	63.36	66.48	66.19	67.88	66.71	65.87	64.92
82	10	0.15	15	1	2	2	91.59	97.76	96.04	91.60	91.61	98.29	92.12	93.34	92.71	91.56
83	10	0.15	15	2	1	3	67.53	69.49	77.98	66.67	70.58	80.59	81.82	68.31	76.88	77.07
84	10	0.15	15	2	2	4	92.29	91.67	98.38	91.66	97.66	99.60	93.04	92.13	91.82	93.40
85	10	0.50	0	1	1	1	161.41	163.52	151.03	168.85	166.65	157.22	138.68	171.83	154.59	155.43

86	10	0.50	0	1	2	2	303.32	305.43	295.53	302.51	280.80	298.94	282.92	280.64	284.05	290.79
87	10	0.50	0	2	1	3	179.69	189.15	176.18	171.20	173.60	181.96	174.19	176.15	196.13	169.71
88	10	0.50	0	2	2	4	301.56	284.81	296.53	285.89	290.72	280.70	283.54	290.83	286.24	280.78
89	10	0.50	7	1	1	1	152.16	171.99	155.40	183.37	154.89	164.50	169.32	170.00	153.54	169.33
90	10	0.50	7	1	2	2	289.04	301.93	294.42	309.84	287.79	300.42	305.90	283.86	285.50	299.07
91	10	0.50	7	2	1	3	170.76	167.31	166.42	180.88	167.63	174.68	163.18	178.66	183.70	183.27
92	10	0.50	7	2	2	4	289.03	286.60	301.56	295.37	288.35	284.36	304.84	298.45	305.62	290.78
93	10	0.50	15	1	1	1	164.82	153.41	155.91	185.03	161.62	149.55	158.10	160.73	150.27	154.37
94	10	0.50	15	1	2	2	306.90	288.39	288.20	288.14	288.35	293.78	294.77	291.09	296.58	288.05
95	10	0.50	15	2	1	3	171.71	188.75	169.25	179.11	186.65	208.65	172.39	169.53	205.02	185.95
96	10	0.50	15	2	2	4	292.91	288.82	296.80	306.80	288.41	301.72	288.25	288.70	300.15	300.03
97	10	0.85	0	1	1	1	253.23	221.56	263.58	221.90	221.60	225.59	222.91	232.51	234.67	227.58
98	10	0.85	0	1	2	2	525.16	479.19	493.65	489.89	492.71	479.12	487.46	486.26	482.47	479.08
99	10	0.85	0	2	1	3	288.67	276.59	262.38	306.43	254.88	250.36	239.64	262.69	282.42	280.62
100	10	0.85	0	2	2	4	496.27	480.10	489.62	492.46	493.79	479.12	479.31	485.69	481.71	516.59
101	10	0.85	7	1	1	1	249.59	228.43	227.64	231.10	228.55	245.62	246.85	264.04	229.89	254.21
102	10	0.85	7	1	2	2	487.02	520.51	494.47	489.14	507.76	491.71	512.01	482.23	514.30	482.17
103	10	0.85	7	2	1	3	280.91	288.23	270.03	246.93	275.77	245.20	293.43	276.67	274.37	283.43
104	10	0.85	7	2	2	4	484.75	516.86	485.23	482.75	506.33	491.79	487.32	505.14	527.44	501.95
105	10	0.85	15	1	1	1	229.60	243.84	223.16	258.30	248.97	237.00	253.39	244.96	222.07	253.77
106	10	0.85	15	1	2	2	492.54	507.81	519.71	489.04	535.44	492.74	487.09	543.84	490.24	487.30
107	10	0.85	15	2	1	3	301.71	278.23	280.06	277.04	271.32	263.22	263.92	303.25	301.10	284.51
108	10	0.85	15	2	2	4	501.49	497.22	489.46	491.76	493.89	514.88	494.06	500.99	487.25	496.53
109	50	0.15	0	1	1	1	84.13	84.04	88.73	86.44	83.98	87.04	89.34	84.01	84.55	84.62
110	50	0.15	0	1	2	2	85.71	85.20	86.24	84.03	88.75	86.48	84.03	84.06	84.02	84.08
111	50	0.15	0	2	1	3	84.47	84.03	91.24	84.01	85.86	85.42	89.18	84.48	84.58	84.02
112	50	0.15	0	2	2	4	84.19	85.23	91.64	90.32	85.74	90.50	86.00	87.05	88.61	88.02
113	50	0.15	7	1	1	1	88.70	90.90	87.08	93.28	88.37	88.22	91.39	91.72	92.80	87.20
114	50	0.15	7	1	2	2	87.14	87.04	93.23	93.27	88.27	93.51	90.34	87.67	87.28	87.66
115	50	0.15	7	2	1	3	92.47	87.12	87.14	91.33	96.02	87.25	89.77	93.38	87.13	91.59

116	50	0.15	7	2	2	4	93.61	87.53	91.85	88.86	87.07	90.12	93.92	87.15	88.40	90.43
117	50	0.15	15	1	1	1	92.82	96.30	94.42	96.11	95.12	95.97	96.26	98.68	92.51	91.80
118	50	0.15	15	1	2	2	95.34	98.39	92.02	94.44	92.94	95.47	96.81	92.06	91.49	93.30
119	50	0.15	15	2	1	3	92.60	92.82	91.46	99.90	93.08	91.63	92.92	94.28	99.25	94.08
120	50	0.15	15	2	2	4	95.76	94.95	98.10	97.69	97.16	91.68	91.82	92.56	94.95	95.03
121	50	0.50	0	1	1	1	256.17	234.13	240.10	281.79	283.97	280.84	237.64	237.17	255.57	230.89
122	50	0.50	0	1	2	2	280.64	281.61	287.25	284.77	300.80	297.74	289.00	303.36	284.94	305.16
123	50	0.50	0	2	1	3	297.18	292.66	281.07	280.69	280.71	288.97	302.99	280.87	280.95	286.46
124	50	0.50	0	2	2	4	283.51	307.59	285.33	305.54	282.23	283.50	294.50	286.16	291.56	280.56
125	50	0.50	7	1	1	1	284.97	257.97	236.54	244.57	242.21	238.19	246.96	234.10	235.01	299.31
126	50	0.50	7	1	2	2	283.84	287.84	301.95	300.78	308.68	283.89	319.26	284.93	302.93	283.80
127	50	0.50	7	2	1	3	286.64	292.91	299.80	288.10	283.98	285.23	283.83	304.34	297.83	306.03
128	50	0.50	7	2	2	4	286.61	283.88	295.56	288.05	299.51	283.98	283.63	287.88	304.92	301.07
129	50	0.50	15	1	1	1	249.13	250.20	236.55	305.64	259.60	251.15	289.82	250.54	290.96	212.14
130	50	0.50	15	1	2	2	321.10	288.12	288.27	294.33	294.22	305.70	299.13	288.11	316.24	297.37
131	50	0.50	15	2	1	3	310.33	311.29	303.60	302.09	303.87	288.28	302.39	288.78	291.08	252.41
132	50	0.50	15	2	2	4	288.23	301.44	291.09	288.32	298.70	288.36	304.13	301.71	307.06	320.42
133	50	0.85	0	1	1	1	329.88	332.55	326.39	337.25	332.67	336.34	321.39	338.93	348.17	353.47
134	50	0.85	0	1	2	2	479.24	495.93	508.43	479.67	517.89	479.69	481.92	479.46	505.65	493.41
135	50	0.85	0	2	1	3	348.59	337.96	339.19	404.58	345.53	333.27	396.19	397.68	327.08	351.56
136	50	0.85	0	2	2	4	496.88	519.09	485.24	539.56	514.75	493.65	482.24	486.43	485.21	482.20
137	50	0.85	7	1	1	1	333.98	326.23	321.90	339.56	336.08	334.14	364.60	344.32	336.88	352.23
138	50	0.85	7	1	2	2	482.17	489.17	482.35	482.21	485.62	520.54	482.68	496.75	505.28	489.74
139	50	0.85	7	2	1	3	358.29	425.59	421.82	343.95	348.41	418.16	395.13	336.14	413.08	337.27
140	50	0.85	7	2	2	4	488.01	485.52	508.86	483.38	509.87	512.14	498.76	507.20	489.81	490.49
141	50	0.85	15	1	1	1	351.26	370.62	336.11	343.25	344.96	362.19	352.93	336.31	351.22	352.75
142	50	0.85	15	1	2	2	490.38	515.94	492.75	521.71	496.44	487.19	487.22	494.39	514.53	525.76
143	50	0.85	15	2	1	3	339.94	339.88	362.63	415.21	334.74	404.34	440.52	377.29	434.19	344.15
144	50	0.85	15	2	2	4	491.90	494.15	517.54	497.35	487.28	520.57	509.66	486.85	494.37	487.36

APPENDIX J: SOLUTIONS # SHORTCUTS FROM THE LLDP TESTING

							Number of Shortcuts for Replication									
Test	Ω	ρ_{LCMHS}	t	θ	S	θS	1	2	3	4	5	6	7	8	9	10
1	0.10	0.15	0	1	1	1	21	21	22	20	23	21	21	21	21	21
2	0.10	0.15	0	1	2	2	22	22	19	21	19	21	19	21	18	21
3	0.10	0.15	0	2	1	3	21	18	20	21	19	19	20	20	19	21
4	0.10	0.15	0	2	2	4	19	21	18	19	20	20	19	21	18	18
5	0.10	0.15	7	1	1	1	21	21	20	21	22	20	21	21	21	21
6	0.10	0.15	7	1	2	2	21	22	19	19	20	18	21	22	17	21
7	0.10	0.15	7	2	1	3	21	20	20	20	22	19	20	20	20	20
8	0.10	0.15	7	2	2	4	20	20	19	21	20	20	21	20	22	21
9	0.10	0.15	15	1	1	1	23	20	22	20	21	19	20	21	21	21
10	0.10	0.15	15	1	2	2	22	21	20	19	20	19	18	21	21	20
11	0.10	0.15	15	2	1	3	21	21	23	21	21	20	20	19	20	21
12	0.10	0.15	15	2	2	4	21	19	19	20	19	19	21	21	20	20
13	0.10	0.50	0	1	1	1	23	21	21	22	22	21	21	23	22	22
14	0.10	0.50	0	1	2	2	23	20	22	20	22	23	22	22	22	23
15	0.10	0.50	0	2	1	3	21	22	22	22	20	21	22	21	21	22
16	0.10	0.50	0	2	2	4	21	22	20	21	22	21	21	22	22	21
17	0.10	0.50	7	1	1	1	21	21	21	20	22	22	22	23	20	22
18	0.10	0.50	7	1	2	2	21	22	22	22	22	22	20	23	22	21
19	0.10	0.50	7	2	1	3	22	22	20	20	22	22	20	22	22	21
20	0.10	0.50	7	2	2	4	23	20	23	21	21	23	21	23	20	22
21	0.10	0.50	15	1	1	1	22	22	21	20	21	22	21	21	22	22
22	0.10	0.50	15	1	2	2	21	22	21	21	19	21	20	21	21	22
23	0.10	0.50	15	2	1	3	22	19	22	22	20	22	21	21	23	20
24	0.10	0.50	15	2	2	4	21	22	23	21	22	23	20	21	22	21
25	0.10	0.85	0	1	1	1	21	20	21	23	21	22	22	22	21	22
26	0.10	0.85	0	1	2	2	22	21	22	21	21	22	20	22	23	22

27	0.10	0.85	0	2	1	3	22	19	22	22	21	21	22	22	23	21
28	0.10	0.85	0	2	2	4	20	22	22	23	21	20	21	24	22	20
29	0.10	0.85	7	1	1	1	21	22	22	22	21	22	22	22	21	23
30	0.10	0.85	7	1	2	2	22	20	22	20	20	23	20	21	20	21
31	0.10	0.85	7	2	1	3	21	22	22	21	20	20	22	21	21	21
32	0.10	0.85	7	2	2	4	22	21	23	21	23	22	21	21	21	22
33	0.10	0.85	15	1	1	1	22	22	22	22	21	21	22	21	20	21
34	0.10	0.85	15	1	2	2	21	22	21	22	21	22	22	23	22	21
35	0.10	0.85	15	2	1	3	23	22	21	22	22	21	23	22	22	20
36	0.10	0.85	15	2	2	4	23	22	22	22	21	21	23	23	22	21
37	1	0.15	0	1	1	1	13	16	14	15	14	13	14	14	12	14
38	1	0.15	0	1	2	2	15	12	15	16	15	15	12	14	16	14
39	1	0.15	0	2	1	3	10	10	9	10	10	10	11	11	10	8
40	1	0.15	0	2	2	4	13	10	13	12	12	12	12	12	13	11
41	1	0.15	7	1	1	1	12	16	13	14	12	13	14	13	12	13
42	1	0.15	7	1	2	2	15	14	14	12	12	14	15	13	13	14
43	1	0.15	7	2	1	3	11	9	10	10	11	9	9	11	12	9
44	1	0.15	7	2	2	4	13	11	12	12	10	11	14	14	12	12
45	1	0.15	15	1	1	1	13	12	14	13	15	14	13	14	14	13
46	1	0.15	15	1	2	2	11	13	12	14	16	14	15	15	15	14
47	1	0.15	15	2	1	3	10	12	10	11	10	12	9	11	11	11
48	1	0.15	15	2	2	4	9	12	12	12	13	14	12	12	11	12
49	1	0.50	0	1	1	1	20	20	20	19	19	20	19	18	20	20
50	1	0.50	0	1	2	2	18	18	18	20	17	19	18	17	20	17
51	1	0.50	0	2	1	3	17	17	15	16	16	16	16	15	18	16
52	1	0.50	0	2	2	4	18	19	17	18	19	16	19	20	15	19
53	1	0.50	7	1	1	1	20	20	20	20	19	20	20	18	20	19
54	1	0.50	7	1	2	2	19	17	19	19	18	19	19	19	18	19
55	1	0.50	7	2	1	3	15	16	16	16	15	14	17	16	17	17
56	1	0.50	7	2	2	4	16	17	19	17	19	19	18	21	17	17

57	1	0.50	15	1	1	1	19	18	19	20	20	19	21	21	19	20
58	1	0.50	15	1	2	2	18	20	19	22	20	18	18	18	17	20
59	1	0.50	15	2	1	3	15	16	15	16	16	17	17	17	15	16
60	1	0.50	15	2	2	4	18	18	16	20	19	20	19	16	17	17
61	1	0.85	0	1	1	1	20	21	21	22	21	21	20	20	20	21
62	1	0.85	0	1	2	2	18	21	20	21	20	20	19	20	20	20
63	1	0.85	0	2	1	3	18	18	19	21	19	17	17	19	18	18
64	1	0.85	0	2	2	4	19	21	19	17	19	18	20	18	19	20
65	1	0.85	7	1	1	1	20	21	21	20	22	20	21	21	21	21
66	1	0.85	7	1	2	2	17	17	19	19	20	20	19	19	20	18
67	1	0.85	7	2	1	3	18	20	19	20	17	20	20	19	19	20
68	1	0.85	7	2	2	4	19	19	20	19	20	19	18	18	20	18
69	1	0.85	15	1	1	1	20	21	21	21	22	20	23	21	21	20
70	1	0.85	15	1	2	2	17	22	19	20	21	22	20	20	20	20
71	1	0.85	15	2	1	3	18	18	18	19	19	19	20	17	19	19
72	1	0.85	15	2	2	4	19	20	19	20	20	19	20	21	19	21
73	10	0.15	0	1	1	1	4	4	4	4	4	4	4	4	4	4
74	10	0.15	0	1	2	2	4	4	4	3	4	4	4	4	4	3
75	10	0.15	0	2	1	3	3	3	3	3	4	3	3	2	3	3
76	10	0.15	0	2	2	4	2	4	2	3	4	3	3	3	3	3
77	10	0.15	7	1	1	1	4	4	4	4	4	4	4	4	4	4
78	10	0.15	7	1	2	2	4	4	4	4	3	4	3	4	4	4
79	10	0.15	7	2	1	3	3	3	4	3	3	3	3	4	4	3
80	10	0.15	7	2	2	4	4	4	3	4	4	4	4	3	4	4
81	10	0.15	15	1	1	1	4	4	4	4	4	4	4	4	4	4
82	10	0.15	15	1	2	2	4	3	4	4	4	4	4	4	4	4
83	10	0.15	15	2	1	3	4	4	3	4	4	3	3	4	3	3
84	10	0.15	15	2	2	4	3	3	4	4	4	3	3	3	4	3
85	10	0.50	0	1	1	1	7	7	7	6	6	7	8	6	8	7
86	10	0.50	0	1	2	2	10	9	5	7	6	8	7	9	7	8

87	10	0.50	0	2	1	3	5	4	5	6	5	5	5	6	4	6
88	10	0.50	0	2	2	4	5	6	5	8	6	7	4	6	6	7
89	10	0.50	7	1	1	1	8	6	8	6	8	6	6	6	7	6
90	10	0.50	7	1	2	2	8	6	6	9	9	7	6	7	7	8
91	10	0.50	7	2	1	3	6	6	6	5	6	6	6	5	5	5
92	10	0.50	7	2	2	4	5	6	7	6	6	5	6	6	7	7
93	10	0.50	15	1	1	1	7	8	8	6	7	8	8	8	8	8
94	10	0.50	15	1	2	2	11	6	5	8	8	8	5	7	7	8
95	10	0.50	15	2	1	3	6	6	6	6	5	4	6	6	4	5
96	10	0.50	15	2	2	4	7	6	6	8	5	7	6	6	8	7
97	10	0.85	0	1	1	1	9	10	8	10	11	10	11	10	10	11
98	10	0.85	0	1	2	2	12	9	11	11	13	13	12	12	11	11
99	10	0.85	0	2	1	3	6	7	7	6	8	8	9	8	6	7
100	10	0.85	0	2	2	4	9	9	8	7	7	10	10	10	10	10
101	10	0.85	7	1	1	1	10	11	10	10	10	10	9	8	10	8
102	10	0.85	7	1	2	2	10	14	9	10	13	11	11	13	11	11
103	10	0.85	7	2	1	3	6	6	7	8	7	8	6	7	7	7
104	10	0.85	7	2	2	4	9	7	9	7	9	10	8	9	12	9
105	10	0.85	15	1	1	1	11	10	11	9	9	10	9	10	11	10
106	10	0.85	15	1	2	2	11	8	12	9	11	11	12	10	11	11
107	10	0.85	15	2	1	3	7	7	7	7	8	7	7	6	6	7
108	10	0.85	15	2	2	4	9	9	9	8	10	9	8	8	9	8
109	50	0.15	0	1	1	1	2	2	2	2	2	2	2	2	2	2
110	50	0.15	0	1	2	2	2	2	2	2	2	2	2	2	2	2
111	50	0.15	0	2	1	3	2	2	2	2	2	2	2	2	2	2
112	50	0.15	0	2	2	4	2	2	2	2	2	2	2	2	2	2
113	50	0.15	7	1	1	1	2	2	2	2	2	2	2	2	2	2
114	50	0.15	7	1	2	2	2	2	2	2	2	2	2	2	2	2
115	50	0.15	7	2	1	3	2	2	2	2	2	2	2	2	2	2
116	50	0.15	7	2	2	4	2	2	2	2	2	2	2	2	2	2

117	50	0.15	15	1	1	1	2	2	2	2	2	2	2	2	2	2
118	50	0.15	15	1	2	2	2	2	2	2	2	2	2	2	2	2
119	50	0.15	15	2	1	3	2	2	2	2	2	2	2	2	2	2
120	50	0.15	15	2	2	4	2	2	2	2	2	2	2	2	2	2
121	50	0.50	0	1	1	1	3	3	3	2	2	2	3	3	3	3
122	50	0.50	0	1	2	2	3	3	3	3	3	3	3	2	3	3
123	50	0.50	0	2	1	3	2	2	2	2	2	2	2	2	2	2
124	50	0.50	0	2	2	4	2	2	3	3	2	2	2	2	2	2
125	50	0.50	7	1	1	1	2	3	3	3	3	3	3	3	3	2
126	50	0.50	7	1	2	2	2	3	2	2	2	3	3	4	2	3
127	50	0.50	7	2	1	3	2	2	2	2	2	2	2	2	2	2
128	50	0.50	7	2	2	4	2	2	2	2	2	3	2	2	3	2
129	50	0.50	15	1	1	1	3	3	3	2	3	3	2	3	2	4
130	50	0.50	15	1	2	2	2	2	2	2	2	3	3	3	3	2
131	50	0.50	15	2	1	3	2	2	2	2	2	2	2	2	2	3
132	50	0.50	15	2	2	4	2	2	2	2	3	3	2	2	3	2
133	50	0.85	0	1	1	1	4	4	4	4	4	4	4	4	4	4
134	50	0.85	0	1	2	2	4	4	4	4	4	4	4	4	4	4
135	50	0.85	0	2	1	3	4	4	4	3	4	4	3	3	4	4
136	50	0.85	0	2	2	4	4	3	4	3	4	4	4	3	4	4
137	50	0.85	7	1	1	1	4	4	4	4	4	4	4	4	4	4
138	50	0.85	7	1	2	2	4	4	4	4	4	4	4	4	4	4
139	50	0.85	7	2	1	3	4	3	3	4	4	3	3	4	3	4
140	50	0.85	7	2	2	4	4	4	4	4	3	4	4	4	3	4
141	50	0.85	15	1	1	1	4	4	4	4	4	4	4	4	4	4
142	50	0.85	15	1	2	2	4	4	4	4	3	4	4	4	4	3
143	50	0.85	15	2	1	3	4	4	4	3	4	3	3	4	3	4
144	50	0.85	15	2	2	4	4	3	3	3	4	4	4	4	3	4

APPENDIX K: SOLUTIONS # ITERATIONS FROM THE LLDP TESTING

Test	Ω	ρ_{LCMHS}	t	θ	S	θS	Number of Iterations for Replication									
							1	2	3	4	5	6	7	8	9	10
1	0.10	0.15	0	1	1	1	1005	1146	1260	896	980	1309	953	1253	870	930
2	0.10	0.15	0	1	2	2	1663	1302	1439	1417	1573	1363	1696	1784	1156	1266
3	0.10	0.15	0	2	1	3	1029	820	751	982	1840	742	1777	955	671	848
4	0.10	0.15	0	2	2	4	1920	827	1765	1088	1197	1221	1615	1304	1064	1553
5	0.10	0.15	7	1	1	1	793	1525	1000	1042	988	884	906	889	789	1413
6	0.10	0.15	7	1	2	2	1275	1657	1441	759	1360	1070	1438	2425	1011	1032
7	0.10	0.15	7	2	1	3	1047	802	962	699	771	856	811	1614	881	850
8	0.10	0.15	7	2	2	4	2484	1724	1793	1838	1148	1416	1127	919	1989	1159
9	0.10	0.15	15	1	1	1	794	955	862	1137	771	976	952	839	952	880
10	0.10	0.15	15	1	2	2	1662	2049	861	1146	932	1010	1003	1175	1576	2190
11	0.10	0.15	15	2	1	3	972	882	810	896	723	1660	666	1216	816	798
12	0.10	0.15	15	2	2	4	1068	1093	1464	1376	827	995	2529	2643	1125	952
13	0.10	0.50	0	1	1	1	1722	2064	798	924	954	1131	783	1234	1328	993
14	0.10	0.50	0	1	2	2	1466	1604	1103	1028	1105	881	1083	2558	1676	1265
15	0.10	0.50	0	2	1	3	1321	964	962	932	1425	1297	1028	1117	928	950
16	0.10	0.50	0	2	2	4	2852	1084	1674	1513	998	1432	853	1705	1509	1036
17	0.10	0.50	7	1	1	1	880	929	890	1718	1714	1936	929	748	950	747
18	0.10	0.50	7	1	2	2	1005	2441	1146	1217	1216	2067	1572	1119	766	2040
19	0.10	0.50	7	2	1	3	824	1119	1327	2127	897	710	823	778	1523	1238
20	0.10	0.50	7	2	2	4	855	1126	943	1412	1124	2092	1147	748	1510	834
21	0.10	0.50	15	1	1	1	1210	770	1150	840	857	1302	1061	678	840	741
22	0.10	0.50	15	1	2	2	1272	1483	1489	1277	809	1538	859	1424	1338	1965
23	0.10	0.50	15	2	1	3	1583	1049	737	838	1063	805	816	1786	1516	1863
24	0.10	0.50	15	2	2	4	1684	1075	985	1871	1149	1584	864	952	848	1079
25	0.10	0.85	0	1	1	1	706	1205	1379	1024	936	1507	1254	928	1137	750
26	0.10	0.85	0	1	2	2	1307	942	838	1536	1688	1772	967	902	2006	1910

27	0.10	0.85	0	2	1	3	1004	935	1332	907	805	837	688	1017	1317	1237
28	0.10	0.85	0	2	2	4	1489	1569	871	1048	2240	1278	1712	2682	1595	1403
29	0.10	0.85	7	1	1	1	861	1433	1256	1006	876	973	1251	1524	903	813
30	0.10	0.85	7	1	2	2	1831	2888	976	1535	1623	953	953	2630	988	2073
31	0.10	0.85	7	2	1	3	1144	845	1358	1239	2302	872	1708	1218	1509	1355
32	0.10	0.85	7	2	2	4	1007	820	3171	953	1650	1785	872	943	967	888
33	0.10	0.85	15	1	1	1	1091	1479	856	1121	760	824	859	935	976	1039
34	0.10	0.85	15	1	2	2	2484	2655	1158	869	1430	1535	2008	1032	1787	1051
35	0.10	0.85	15	2	1	3	798	1011	692	893	776	834	1383	1130	1044	861
36	0.10	0.85	15	2	2	4	1424	2726	925	960	970	1509	1182	1652	1166	1685
37	1	0.15	0	1	1	1	1015	1417	1126	1390	677	930	1674	1418	1398	726
38	1	0.15	0	1	2	2	1247	1657	975	1021	1153	942	1118	2256	932	924
39	1	0.15	0	2	1	3	1027	1625	1101	892	766	1304	1104	831	1284	1305
40	1	0.15	0	2	2	4	1015	2534	987	2396	1400	1633	1464	1101	1084	1133
41	1	0.15	7	1	1	1	1673	1483	1243	925	1294	672	1189	741	1095	594
42	1	0.15	7	1	2	2	854	892	2074	769	1420	1183	1206	1022	1815	2045
43	1	0.15	7	2	1	3	851	807	2214	1244	1135	1228	673	932	1816	880
44	1	0.15	7	2	2	4	1032	986	1082	1185	959	1467	1624	2207	1398	900
45	1	0.15	15	1	1	1	809	947	1380	877	998	1636	1132	912	910	1146
46	1	0.15	15	1	2	2	1058	1551	954	1311	771	1456	1864	2465	919	1253
47	1	0.15	15	2	1	3	1000	725	1482	661	1154	929	1041	1437	964	805
48	1	0.15	15	2	2	4	1664	1686	1960	1509	1289	847	2428	1449	1835	714
49	1	0.50	0	1	1	1	814	723	902	977	1279	874	787	724	718	955
50	1	0.50	0	1	2	2	1816	2698	1597	789	1530	839	2087	1211	1382	2415
51	1	0.50	0	2	1	3	1388	1413	1222	1501	1695	693	1007	789	1195	1941
52	1	0.50	0	2	2	4	1383	2087	1085	1693	1566	1365	1153	1142	985	1432
53	1	0.50	7	1	1	1	960	1374	1497	1490	2716	813	962	846	1115	822
54	1	0.50	7	1	2	2	2048	1563	2797	910	2633	1262	1003	828	2987	1412
55	1	0.50	7	2	1	3	798	1901	758	1257	788	988	1170	927	866	696
56	1	0.50	7	2	2	4	1690	4024	1744	1165	1836	1349	1285	1201	1038	1799

57	1	0.50	15	1	1	1	1132	1441	1184	903	1114	1039	876	941	634	1707
58	1	0.50	15	1	2	2	1181	959	774	1096	1008	1061	1919	930	2446	873
59	1	0.50	15	2	1	3	972	729	897	1294	1239	939	1443	1315	1284	1097
60	1	0.50	15	2	2	4	862	1355	1341	1323	980	913	2339	1482	1342	832
61	1	0.85	0	1	1	1	1131	2244	789	1672	1507	785	1192	914	867	2167
62	1	0.85	0	1	2	2	1014	1585	2235	986	1276	1418	1456	808	1632	1363
63	1	0.85	0	2	1	3	711	935	1193	1619	1722	733	1494	740	1284	795
64	1	0.85	0	2	2	4	904	1496	951	1828	1062	1452	1654	1303	837	1892
65	1	0.85	7	1	1	1	1271	901	1514	1074	1093	1397	898	898	911	1755
66	1	0.85	7	1	2	2	1004	1543	1734	1403	1677	1824	980	1293	996	1191
67	1	0.85	7	2	1	3	811	1150	1008	680	883	926	1207	841	1378	781
68	1	0.85	7	2	2	4	1757	1489	1010	1553	1208	1133	2494	1145	1872	1342
69	1	0.85	15	1	1	1	807	2192	1009	871	862	742	806	892	1028	715
70	1	0.85	15	1	2	2	807	3994	1411	1115	1141	1402	1368	1591	2686	1008
71	1	0.85	15	2	1	3	1263	830	1594	1221	893	910	1417	901	804	754
72	1	0.85	15	2	2	4	2190	1389	853	1855	1167	1502	1733	989	1239	1735
73	10	0.15	0	1	1	1	861	810	1213	2050	768	976	1007	1544	1089	690
74	10	0.15	0	1	2	2	779	1386	930	1083	883	1867	1447	1932	930	1708
75	10	0.15	0	2	1	3	1246	790	728	1146	1112	1970	1201	1263	1543	1084
76	10	0.15	0	2	2	4	1396	895	1030	1483	1849	1089	1206	2098	1714	1088
77	10	0.15	7	1	1	1	874	2498	942	976	1608	1359	2028	1634	825	840
78	10	0.15	7	1	2	2	1056	1894	1254	1199	2000	1491	748	896	899	1308
79	10	0.15	7	2	1	3	1072	1405	938	1453	952	1724	779	777	805	1308
80	10	0.15	7	2	2	4	1020	1699	1026	1840	1529	1616	1248	948	2031	1079
81	10	0.15	15	1	1	1	1844	892	903	1500	2236	1712	1004	1652	1343	1772
82	10	0.15	15	1	2	2	1217	1170	1246	1140	1507	1152	1212	846	997	2233
83	10	0.15	15	2	1	3	1851	745	1756	1219	1616	1005	946	1022	1483	1373
84	10	0.15	15	2	2	4	1120	971	1017	1474	2257	921	947	948	1039	930
85	10	0.50	0	1	1	1	1574	793	1230	1374	831	909	722	1067	1061	1799
86	10	0.50	0	1	2	2	1089	1626	840	2125	2697	938	1257	936	2158	839

87	10	0.50	0	2	1	3	1149	826	1147	717	1357	1189	2139	748	951	985
88	10	0.50	0	2	2	4	867	1322	1005	1245	1163	1424	1268	1142	1131	2296
89	10	0.50	7	1	1	1	1196	760	1004	1322	1248	2059	1400	1522	1348	1101
90	10	0.50	7	1	2	2	1155	1327	1905	1315	1346	1862	1016	2378	2084	1409
91	10	0.50	7	2	1	3	2959	953	1564	938	1208	995	1492	1246	980	1323
92	10	0.50	7	2	2	4	1092	1428	836	1799	1663	1166	884	1131	796	923
93	10	0.50	15	1	1	1	904	809	1019	1069	1889	981	909	765	1575	1340
94	10	0.50	15	1	2	2	1084	1717	1517	1428	1404	1350	952	1316	1491	2165
95	10	0.50	15	2	1	3	934	1895	890	900	1425	1410	1667	753	741	1376
96	10	0.50	15	2	2	4	1172	1913	1164	1235	1750	1322	1229	1230	1432	1046
97	10	0.85	0	1	1	1	2470	1124	727	756	769	922	1338	1030	893	761
98	10	0.85	0	1	2	2	1372	1356	845	1490	1679	2282	1545	939	1827	1377
99	10	0.85	0	2	1	3	1223	1351	1056	646	2144	2074	776	729	833	884
100	10	0.85	0	2	2	4	1299	1238	1038	718	1235	1556	1033	1217	1504	1030
101	10	0.85	7	1	1	1	1246	1191	723	858	1077	717	1965	715	1708	1270
102	10	0.85	7	1	2	2	1072	1200	1100	1314	1280	923	1788	1160	1550	1814
103	10	0.85	7	2	1	3	798	1333	793	1208	1321	708	1343	907	1009	1288
104	10	0.85	7	2	2	4	1827	1164	1179	1422	1040	1397	1292	1858	968	1306
105	10	0.85	15	1	1	1	788	850	1149	940	814	1856	1086	1482	1014	1029
106	10	0.85	15	1	2	2	1978	1986	1110	2319	1784	1343	911	1239	1270	2499
107	10	0.85	15	2	1	3	967	960	990	1087	1571	1088	2329	1498	998	864
108	10	0.85	15	2	2	4	971	1426	1701	1211	990	2635	1880	1097	1546	1823
109	50	0.15	0	1	1	1	1356	1084	1445	1037	1867	1315	1821	1093	3456	1160
110	50	0.15	0	1	2	2	1098	1047	900	1109	743	867	1535	1862	1484	1279
111	50	0.15	0	2	1	3	1576	1365	907	1050	1576	1711	1291	1337	1988	1528
112	50	0.15	0	2	2	4	1456	1286	750	917	1654	1706	1822	907	905	1099
113	50	0.15	7	1	1	1	1005	1145	1264	767	1152	1323	1205	938	1253	1604
114	50	0.15	7	1	2	2	1057	1359	1122	1173	1385	834	1280	1340	1862	859
115	50	0.15	7	2	1	3	1040	2400	966	1327	772	1167	1998	1117	1032	969
116	50	0.15	7	2	2	4	1372	2065	1470	1838	1005	801	1928	1432	1861	1850

117	50	0.15	15	1	1	1	2649	1890	1660	866	822	828	864	1460	3377	1210
118	50	0.15	15	1	2	2	1395	1470	1426	1278	1623	1622	1066	1956	1377	1302
119	50	0.15	15	2	1	3	1268	2269	2036	1047	2054	1522	1909	1579	1036	887
120	50	0.15	15	2	2	4	822	1275	939	1258	1086	1642	2292	1668	1267	1987
121	50	0.50	0	1	1	1	887	2190	786	964	999	1898	1002	2378	927	1041
122	50	0.50	0	1	2	2	1461	2271	1239	2064	1358	1523	1330	1095	2619	1123
123	50	0.50	0	2	1	3	1150	1078	1765	1324	2307	881	1366	1046	1740	1290
124	50	0.50	0	2	2	4	706	1720	1091	1135	806	1467	1134	1311	1182	1843
125	50	0.50	7	1	1	1	834	898	1795	1986	916	935	841	939	1521	1415
126	50	0.50	7	1	2	2	969	1251	1362	721	845	1596	1742	1419	3264	1049
127	50	0.50	7	2	1	3	1081	763	1519	1554	2162	1090	962	1387	1009	956
128	50	0.50	7	2	2	4	1368	1004	1535	2592	1137	2038	1410	1410	869	1311
129	50	0.50	15	1	1	1	1171	1023	2143	1464	1357	805	752	1095	1539	1449
130	50	0.50	15	1	2	2	1863	1489	2239	1184	1091	1120	1196	1337	760	759
131	50	0.50	15	2	1	3	1010	1062	1831	922	1926	2059	1386	2272	788	1063
132	50	0.50	15	2	2	4	2994	1145	1427	1374	1539	1140	1515	1175	794	862
133	50	0.85	0	1	1	1	1084	1063	980	920	1536	1748	1222	1000	902	1442
134	50	0.85	0	1	2	2	3190	1208	1198	747	1760	897	1227	1266	961	1769
135	50	0.85	0	2	1	3	1351	983	930	1206	938	929	2416	1245	2511	722
136	50	0.85	0	2	2	4	1114	852	2115	889	1872	1216	1192	2712	1585	1408
137	50	0.85	7	1	1	1	1012	1101	1337	1822	932	927	1166	1044	795	1149
138	50	0.85	7	1	2	2	2027	1071	1071	3003	1665	874	1737	2826	1244	1052
139	50	0.85	7	2	1	3	1133	1359	860	844	1827	2010	1327	957	1075	1351
140	50	0.85	7	2	2	4	2395	1828	2132	865	1150	902	1020	1005	1473	1344
141	50	0.85	15	1	1	1	847	682	1749	1431	1355	1133	1271	1654	874	737
142	50	0.85	15	1	2	2	985	1334	1125	1233	1074	1926	967	959	944	1340
143	50	0.85	15	2	1	3	1434	1287	1179	1738	1485	1495	1569	931	976	819
144	50	0.85	15	2	2	4	1563	2254	1075	1207	866	792	1330	1790	1178	875

APPENDIX L: SOLUTION TIMES (MINUTES) FROM THE LLDP TESTING

							Solution Time (minutes) for Replication									
Test	Ω	ρ_{LCMHS}	t	θ	S	θS	1	2	3	4	5	6	7	8	9	10
1	0.10	0.15	0	1	1	1	45.03	59.45	60.22	40.33	44.33	61.93	45.60	55.87	41.02	44.43
2	0.10	0.15	0	1	2	2	37.37	32.42	34.95	35.75	40.47	33.80	48.87	50.77	30.40	29.23
3	0.10	0.15	0	2	1	3	51.12	36.90	32.83	45.43	93.70	35.92	83.27	51.33	30.35	42.12
4	0.10	0.15	0	2	2	4	59.28	23.75	48.12	31.28	30.45	31.62	44.93	34.57	26.52	38.85
5	0.10	0.15	7	1	1	1	33.00	72.40	47.67	46.98	46.87	42.23	43.03	44.68	35.10	69.63
6	0.10	0.15	7	1	2	2	31.30	43.92	41.60	18.67	30.92	26.77	37.47	85.23	36.48	28.00
7	0.10	0.15	7	2	1	3	55.90	41.25	46.62	34.73	38.08	43.83	44.95	92.55	50.63	45.12
8	0.10	0.15	7	2	2	4	86.25	61.37	59.62	56.40	33.43	38.30	29.53	22.48	54.52	35.03
9	0.10	0.15	15	1	1	1	33.30	44.02	39.15	50.65	35.38	44.70	44.97	36.25	44.43	39.48
10	0.10	0.15	15	1	2	2	37.50	51.33	20.55	22.88	19.13	21.10	20.03	25.80	37.80	65.98
11	0.10	0.15	15	2	1	3	52.48	42.85	37.10	40.33	32.45	80.98	30.08	57.13	37.42	35.10
12	0.10	0.15	15	2	2	4	21.08	24.15	35.55	36.57	18.77	21.70	80.10	100.78	36.85	23.25
13	0.10	0.50	0	1	1	1	134.33	172.23	57.82	63.92	66.17	79.27	55.23	84.65	93.98	69.45
14	0.10	0.50	0	1	2	2	53.72	64.83	44.20	35.48	38.97	29.82	35.78	112.45	84.48	54.43
15	0.10	0.50	0	2	1	3	100.32	82.20	72.48	66.03	102.20	100.28	73.32	82.30	63.87	64.05
16	0.10	0.50	0	2	2	4	135.92	49.70	69.13	65.20	36.53	39.98	24.87	53.58	41.13	32.03
17	0.10	0.50	7	1	1	1	60.08	76.45	75.00	125.48	139.25	164.05	66.80	48.35	64.50	49.68
18	0.10	0.50	7	1	2	2	33.37	101.48	51.38	44.82	44.92	81.60	66.07	44.20	25.33	81.13
19	0.10	0.50	7	2	1	3	65.12	85.20	103.22	174.80	68.50	47.33	56.38	52.63	110.55	95.38
20	0.10	0.50	7	2	2	4	30.83	40.13	31.98	48.42	42.37	85.75	39.82	19.55	44.90	24.32
21	0.10	0.50	15	1	1	1	91.83	70.20	91.73	61.35	60.37	89.02	75.67	44.95	58.17	49.82
22	0.10	0.50	15	1	2	2	44.13	55.97	55.97	50.55	27.98	56.83	31.67	54.48	51.35	77.85
23	0.10	0.50	15	2	1	3	127.07	77.05	48.50	60.20	88.57	59.90	55.97	133.92	117.88	140.25
24	0.10	0.50	15	2	2	4	76.77	43.17	35.28	75.78	47.82	63.28	32.97	30.63	27.52	39.40
25	0.10	0.85	0	1	1	1	35.93	74.57	91.73	61.57	49.73	86.05	71.77	52.37	61.28	39.53
26	0.10	0.85	0	1	2	2	33.50	25.95	20.15	40.82	53.32	55.05	29.13	23.47	62.60	66.42

27	0.10	0.85	0	2	1	3	58.97	49.43	70.38	50.92	42.82	41.83	35.55	52.08	73.95	71.57
28	0.10	0.85	0	2	2	4	42.73	46.42	23.97	26.97	74.60	42.48	51.58	96.23	55.98	33.60
29	0.10	0.85	7	1	1	1	44.47	87.28	74.82	58.63	46.67	53.20	67.50	86.40	51.47	44.22
30	0.10	0.85	7	1	2	2	54.20	108.37	34.27	42.67	51.38	27.93	24.48	89.85	34.03	64.23
31	0.10	0.85	7	2	1	3	68.40	45.37	74.77	68.35	137.25	51.52	97.65	72.18	85.50	80.88
32	0.10	0.85	7	2	2	4	27.95	19.80	105.82	24.83	32.08	40.98	24.38	23.18	24.27	22.28
33	0.10	0.85	15	1	1	1	57.97	90.17	53.63	64.35	39.13	42.97	46.30	49.70	50.70	55.62
34	0.10	0.85	15	1	2	2	83.30	108.32	40.53	23.05	39.02	47.12	68.10	33.00	53.33	33.02
35	0.10	0.85	15	2	1	3	41.35	53.33	35.27	47.47	41.40	44.07	78.08	61.10	61.13	47.37
36	0.10	0.85	15	2	2	4	40.47	98.42	31.73	25.33	25.43	45.20	34.57	49.45	34.65	48.98
37	1	0.15	0	1	1	1	52.07	75.78	64.73	80.53	37.60	291.42	102.60	89.78	80.13	41.85
38	1	0.15	0	1	2	2	31.93	51.45	29.63	24.97	32.22	24.42	28.85	73.90	30.78	23.13
39	1	0.15	0	2	1	3	58.18	97.57	65.13	48.25	43.78	71.88	64.95	49.68	77.77	75.75
40	1	0.15	0	2	2	4	27.42	87.77	33.33	83.32	48.00	49.03	46.33	32.02	22.82	20.90
41	1	0.15	7	1	1	1	96.42	97.87	78.45	54.50	308.52	37.73	67.83	39.83	60.33	29.02
42	1	0.15	7	1	2	2	19.32	23.00	64.30	22.05	36.68	34.10	34.03	26.65	54.12	66.10
43	1	0.15	7	2	1	3	50.43	43.35	134.83	76.23	65.03	73.98	37.87	54.50	108.13	51.07
44	1	0.15	7	2	2	4	27.05	25.18	28.22	32.50	26.42	43.58	50.28	71.05	49.60	25.98
45	1	0.15	15	1	1	1	41.22	56.03	86.58	54.55	52.17	334.80	67.72	50.17	49.73	61.62
46	1	0.15	15	1	2	2	28.87	44.25	27.42	39.00	20.83	39.60	61.40	91.40	29.83	30.12
47	1	0.15	15	2	1	3	61.18	36.90	86.27	36.25	64.18	52.15	58.77	86.12	55.88	44.08
48	1	0.15	15	2	2	4	51.05	52.12	60.70	48.42	37.45	23.10	84.37	53.80	53.78	15.83
49	1	0.50	0	1	1	1	41.80	44.75	57.00	62.43	80.65	50.15	40.48	40.52	37.18	52.80
50	1	0.50	0	1	2	2	53.37	96.20	56.87	23.75	46.33	23.37	65.88	39.97	41.22	82.95
51	1	0.50	0	2	1	3	89.63	87.97	73.35	91.05	100.98	40.27	51.98	43.02	69.27	115.03
52	1	0.50	0	2	2	4	45.48	69.85	35.80	50.68	51.82	39.73	30.90	32.42	27.25	40.92
53	1	0.50	7	1	1	1	53.00	89.68	95.63	91.58	181.32	54.00	51.37	46.98	63.88	46.60
54	1	0.50	7	1	2	2	62.12	52.38	100.22	33.35	91.80	46.13	29.02	22.77	108.53	52.95
55	1	0.50	7	2	1	3	48.08	111.43	46.73	73.60	44.57	54.12	71.10	54.53	48.58	38.22
56	1	0.50	7	2	2	4	49.73	177.50	66.93	29.53	47.17	36.72	31.03	27.57	23.10	42.70

57	1	0.50	15	1	1	1	57.62	75.98	65.02	46.07	58.80	56.32	48.50	49.95	31.82	94.33
58	1	0.50	15	1	2	2	33.72	25.80	18.30	28.10	25.65	28.60	60.05	30.18	78.08	28.13
59	1	0.50	15	2	1	3	54.05	38.35	48.72	74.77	71.62	52.70	76.00	75.28	73.58	61.58
60	1	0.50	15	2	2	4	21.45	33.75	38.48	38.37	25.80	22.62	74.32	53.63	41.25	21.28
61	1	0.85	0	1	1	1	58.75	134.78	46.30	93.70	85.32	41.40	64.03	50.75	47.85	123.05
62	1	0.85	0	1	2	2	30.40	45.43	75.33	30.38	35.40	39.92	42.92	20.63	45.42	43.35
63	1	0.85	0	2	1	3	38.35	47.63	64.25	96.80	101.90	40.53	81.80	39.45	70.02	43.38
64	1	0.85	0	2	2	4	22.77	42.83	27.67	54.68	27.83	31.98	42.85	26.37	14.83	37.20
65	1	0.85	7	1	1	1	69.53	47.45	83.03	62.12	60.33	80.18	49.35	45.05	48.43	107.17
66	1	0.85	7	1	2	2	29.17	44.68	54.43	43.12	51.32	58.12	29.57	35.98	28.10	32.03
67	1	0.85	7	2	1	3	44.73	63.32	54.78	34.03	45.80	49.05	66.75	48.50	79.45	43.88
68	1	0.85	7	2	2	4	49.47	46.92	28.63	42.40	35.32	32.60	87.05	35.68	45.08	37.15
69	1	0.85	15	1	1	1	42.02	130.77	60.90	48.57	45.98	38.38	41.73	48.83	56.03	39.27
70	1	0.85	15	1	2	2	18.08	159.35	58.07	32.53	30.90	39.77	39.85	48.73	98.57	32.82
71	1	0.85	15	2	1	3	70.37	46.43	87.70	74.07	50.48	50.27	75.25	51.00	45.33	40.77
72	1	0.85	15	2	2	4	66.40	46.92	22.83	57.20	38.05	44.25	55.33	28.92	34.97	54.87
73	10	0.15	0	1	1	1	51.80	48.82	80.80	147.10	48.73	54.87	61.42	93.35	71.95	40.20
74	10	0.15	0	1	2	2	17.65	38.87	26.80	28.40	23.28	56.82	48.82	65.77	29.48	52.72
75	10	0.15	0	2	1	3	83.10	46.88	40.53	75.47	72.77	129.77	82.55	80.15	99.95	72.48
76	10	0.15	0	2	2	4	40.88	24.65	26.50	41.77	59.12	34.02	33.97	59.10	47.70	27.62
77	10	0.15	7	1	1	1	51.43	191.83	65.32	60.25	100.97	90.18	142.75	110.28	52.90	49.18
78	10	0.15	7	1	2	2	27.35	57.68	38.63	34.03	63.72	48.72	19.77	21.38	22.83	35.32
79	10	0.15	7	2	1	3	69.98	92.67	58.27	93.23	60.85	106.57	47.98	44.88	47.72	85.82
80	10	0.15	7	2	2	4	28.72	48.72	30.70	53.60	40.55	43.08	30.75	17.08	41.82	23.40
81	10	0.15	15	1	1	1	111.42	55.68	53.60	89.10	142.45	116.98	65.55	108.25	84.23	117.98
82	10	0.15	15	1	2	2	37.25	33.20	34.72	30.60	42.75	32.90	33.10	21.67	23.97	73.48
83	10	0.15	15	2	1	3	134.57	44.63	114.65	77.07	104.52	61.68	56.37	61.55	91.00	88.18
84	10	0.15	15	2	2	4	30.28	21.55	20.48	31.60	58.78	22.73	18.23	19.03	21.38	17.90
85	10	0.50	0	1	1	1	96.72	45.63	68.87	78.47	47.67	52.50	38.68	57.35	65.13	109.78
86	10	0.50	0	1	2	2	30.32	50.02	23.97	66.08	96.52	30.65	33.38	25.43	65.87	24.75

87	10	0.50	0	2	1	3	67.88	47.90	68.35	41.43	81.35	75.07	143.70	45.42	54.68	59.38
88	10	0.50	0	2	2	4	20.78	32.57	25.88	33.83	33.60	40.33	37.60	31.55	31.45	74.93
89	10	0.50	7	1	1	1	63.67	43.93	53.98	78.05	73.07	128.40	91.15	92.02	83.67	66.75
90	10	0.50	7	1	2	2	30.52	36.95	55.40	39.65	36.12	56.80	31.63	77.92	76.53	44.38
91	10	0.50	7	2	1	3	201.05	63.58	101.32	55.43	72.90	60.38	90.47	81.97	59.70	80.68
92	10	0.50	7	2	2	4	31.23	33.25	17.80	41.10	42.35	28.53	17.48	22.35	15.50	18.53
93	10	0.50	15	1	1	1	46.48	45.62	60.17	61.45	103.25	51.68	45.17	36.30	87.40	72.90
94	10	0.50	15	1	2	2	26.00	44.32	41.62	36.22	33.88	33.02	20.77	30.60	36.02	62.92
95	10	0.50	15	2	1	3	56.22	111.20	51.90	50.13	82.68	79.87	94.30	40.17	37.80	75.52
96	10	0.50	15	2	2	4	26.62	44.95	28.62	27.97	46.32	35.92	29.70	28.85	32.62	22.98
97	10	0.85	0	1	1	1	149.18	59.68	34.50	34.45	35.95	44.98	63.48	53.37	44.68	35.95
98	10	0.85	0	1	2	2	27.50	31.85	18.03	33.80	40.80	69.70	48.53	22.83	47.20	36.48
99	10	0.85	0	2	1	3	69.52	77.72	62.82	32.35	128.37	127.53	45.20	36.93	42.95	47.22
100	10	0.85	0	2	2	4	27.80	28.40	22.98	13.17	25.63	40.28	25.57	27.62	39.47	22.78
101	10	0.85	7	1	1	1	64.10	63.52	37.48	45.90	55.27	33.32	102.48	38.10	87.98	67.52
102	10	0.85	7	1	2	2	24.33	26.12	24.93	27.88	30.60	19.30	45.80	31.12	38.67	47.55
103	10	0.85	7	2	1	3	42.35	72.02	40.43	63.75	69.87	34.57	66.47	47.47	48.85	68.37
104	10	0.85	7	2	2	4	44.60	30.07	27.10	33.92	24.93	34.00	30.92	54.03	27.58	33.70
105	10	0.85	15	1	1	1	40.67	49.83	68.88	62.50	47.23	105.80	66.93	81.27	59.40	62.63
106	10	0.85	15	1	2	2	58.30	68.62	37.83	76.38	60.73	42.78	25.42	34.10	37.55	87.45
107	10	0.85	15	2	1	3	64.80	56.23	58.70	65.80	100.92	67.83	151.33	105.00	61.75	48.05
108	10	0.85	15	2	2	4	24.77	40.20	52.70	35.42	26.30	87.13	72.20	34.98	43.50	60.62
109	50	0.15	0	1	1	1	89.80	79.65	102.03	68.38	126.15	86.77	123.97	75.05	274.00	91.72
110	50	0.15	0	1	2	2	30.35	27.68	23.15	29.85	18.83	20.95	47.40	64.02	51.87	39.73
111	50	0.15	0	2	1	3	101.40	96.15	60.35	65.87	108.77	115.22	89.00	92.35	138.92	105.80
112	50	0.15	0	2	2	4	30.35	24.77	12.08	14.83	32.92	36.60	38.97	17.63	14.97	19.30
113	50	0.15	7	1	1	1	61.67	74.72	88.57	47.98	71.57	83.43	76.18	58.93	80.83	104.80
114	50	0.15	7	1	2	2	31.37	38.78	29.52	33.03	39.60	23.72	34.27	39.58	60.03	24.72
115	50	0.15	7	2	1	3	67.68	172.18	68.13	86.82	46.37	70.38	130.48	77.00	64.55	59.48
116	50	0.15	7	2	2	4	38.15	66.73	48.00	56.38	30.62	20.45	58.60	47.08	59.25	63.55

117	50	0.15	15	1	1	1	177.63	114.75	117.57	56.63	50.25	49.25	52.73	95.17	270.97	88.38
118	50	0.15	15	1	2	2	39.32	41.53	41.55	37.77	48.00	53.28	31.92	60.52	46.85	38.13
119	50	0.15	15	2	1	3	79.87	156.48	146.83	70.23	131.93	115.57	136.43	106.40	68.40	44.28
120	50	0.15	15	2	2	4	16.23	26.32	20.28	27.48	24.67	38.82	64.78	47.38	30.78	43.03
121	50	0.50	0	1	1	1	53.05	158.32	52.03	59.03	57.53	129.38	67.28	160.67	61.77	64.10
122	50	0.50	0	1	2	2	43.08	77.10	42.08	64.00	43.18	45.05	40.47	32.03	92.45	40.10
123	50	0.50	0	2	1	3	73.68	70.60	119.90	87.75	164.23	63.92	89.90	65.55	117.65	65.27
124	50	0.50	0	2	2	4	13.45	39.70	25.55	23.85	15.73	31.97	26.32	28.90	25.97	43.73
125	50	0.50	7	1	1	1	48.55	55.58	102.57	121.67	62.10	54.73	49.77	59.73	97.07	92.15
126	50	0.50	7	1	2	2	28.53	37.02	40.97	19.92	20.78	48.03	56.63	46.72	122.28	40.40
127	50	0.50	7	2	1	3	70.03	45.77	94.82	104.10	154.17	77.67	61.42	95.90	65.12	60.77
128	50	0.50	7	2	2	4	39.87	28.65	46.00	98.90	40.13	69.13	49.22	45.22	23.88	36.37
129	50	0.50	15	1	1	1	72.57	64.47	150.23	103.08	90.00	48.77	44.72	71.67	102.28	90.95
130	50	0.50	15	1	2	2	58.75	47.75	76.60	40.55	31.42	30.02	32.17	41.10	23.00	17.63
131	50	0.50	15	2	1	3	61.93	69.77	125.00	60.20	133.65	148.75	98.65	163.20	51.77	62.32
132	50	0.50	15	2	2	4	95.00	36.77	33.68	35.15	38.70	27.98	31.77	22.52	12.72	14.15
133	50	0.85	0	1	1	1	64.57	71.17	64.93	56.88	94.40	114.20	77.30	63.30	55.67	86.18
134	50	0.85	0	1	2	2	121.58	44.42	34.83	21.72	45.80	24.58	30.65	35.27	26.13	51.15
135	50	0.85	0	2	1	3	89.72	63.37	54.97	73.60	55.35	53.57	161.77	90.42	185.58	50.47
136	50	0.85	0	2	2	4	27.52	21.68	64.30	27.10	54.43	31.97	26.77	73.73	49.47	32.78
137	50	0.85	7	1	1	1	57.58	72.60	88.17	116.03	58.23	56.87	66.52	65.28	47.75	68.57
138	50	0.85	7	1	2	2	63.73	35.07	30.17	111.32	67.12	25.43	51.05	103.15	43.20	28.27
139	50	0.85	7	2	1	3	71.13	88.13	54.33	48.28	112.27	133.78	87.92	60.93	66.72	84.13
140	50	0.85	7	2	2	4	84.27	71.77	69.77	20.98	24.25	19.08	20.92	22.55	33.48	32.35
141	50	0.85	15	1	1	1	48.77	39.55	116.30	95.58	84.50	71.07	73.53	108.23	52.88	41.10
142	50	0.85	15	1	2	2	24.55	34.23	31.13	33.20	29.72	66.25	31.33	24.08	23.62	36.32
143	50	0.85	15	2	1	3	90.52	82.73	73.03	111.57	97.40	93.37	98.98	57.95	57.82	48.32
144	50	0.85	15	2	2	4	42.85	72.58	35.12	33.28	22.75	19.60	34.98	55.90	36.47	23.37

APPENDIX M: GLM PROCEDURE SAS OUTPUT FOR THE LLDP

```
                      The SAS System
1

                     The GLM Procedure

                   Class Level Information

               Class        Levels  Values
               Omega          4  0.1 1 10 50
               Rho           3  0.15 0.5 0.85
               ttime          3  0 7 15
               Opt_Criteria       2  1 2
               Shortcut         2  1 2
               Scenario         4  1 2 3 4


                  Number of observations  1440

                      The SAS System
2

                     The GLM Procedure

Dependent Variable: WIP  Work in Process

                        Sum of
    Source            DF      Squares   Mean Square  F Value  Pr > F
    Model             10   28900516.50   2890051.65   946.64  <.0001
    Error           1429   4362668.53     3052.95
    Corrected Total      1439   33263185.03


             R-Square   Coeff Var   Root MSE   WIP Mean
             0.868844   24.45181   55.25353   225.9690


    Source            DF     Type I SS    Mean Square  F Value  Pr > F
    Omega             3    959386.36    319795.45   104.75  <.0001
    Rho             2   21353416.52   10676708.26  3497.18  <.0001
    ttime             2    14083.68     7041.84     2.31  0.1000
    Opt_Criteria         1     19252.11     19252.11     6.31  0.0121
    Shortcut           1   6537435.99   6537435.99  2141.35  <.0001
    Scenario           1    16941.83    16941.83     5.55  0.0186


    Source            DF   Type III SS   Mean Square  F Value  Pr > F
    Omega             3    959386.36    319795.45   104.75  <.0001
    Rho             2   21353416.52   10676708.26  3497.18  <.0001
    ttime             2    14083.68     7041.84     2.31  0.1000
    Opt_Criteria         0       0.00        .      .    .
    Shortcut           0       0.00        .      .    .
    Scenario           1    16941.83    16941.83     5.55  0.0186

                      The SAS System
3
```

```
                     The GLM Procedure

              Tukey's Studentized Range (HSD) Test for WIP

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                    II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom        1429
              Error Mean Square          3052.952
              Critical Value of Studentized Range 3.63754
              Minimum Significant Difference    10.593


          Means with the same letter are not significantly different.


           Tukey Grouping     Mean   N  Omega
                 A    267.046  360  50
                 B    228.877  360  10
                 C    204.933  360  1
                 C    203.020  360  0.1

                      The SAS System
4

                     The GLM Procedure

              Tukey's Studentized Range (HSD) Test for WIP

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                    II error rate than REGWQ.


              Alpha                   0.05
              Error Degrees of Freedom        1429
              Error Mean Square          3052.952
              Critical Value of Studentized Range 3.31796
              Minimum Significant Difference    8.3678


           Means with the same letter are not significantly different.


           Tukey Grouping     Mean   N  Rho
                  A    372.840  480  0.85
                  B    230.411  480  0.5
                  C    74.656  480  0.15

                      The SAS System
5
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```
                     The GLM Procedure

              Tukey's Studentized Range (HSD) Test for WIP

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                  0.05
              Error Degrees of Freedom        1429
              Error Mean Square          3052.952
              Critical Value of Studentized Range 3.31796
              Minimum Significant Difference    8.3678


          Means with the same letter are not significantly different.


           Tukey Grouping     Mean   N  ttime

                 A    229.915  480  15
                 A    225.725  480  7
                 A    222.266  480  0

                      The SAS System
6

                     The GLM Procedure

              Tukey's Studentized Range (HSD) Test for WIP

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                   II error rate than REGWQ.


              Alpha                  0.05
              Error Degrees of Freedom        1429
              Error Mean Square          3052.952
              Critical Value of Studentized Range 2.77416
              Minimum Significant Difference    5.7125


           Means with the same letter are not significantly different.


                             Opt_
          Tukey Grouping     Mean   N  Criteria
                 A    229.625  720  2
                 B    222.313  720  1

                      The SAS System
7

                     The GLM Procedure
```

```
             Tukey's Studentized Range (HSD) Test for WIP

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                  II error rate than REGWQ.


             Alpha                   0.05
             Error Degrees of Freedom        1429
             Error Mean Square          3052.952
             Critical Value of Studentized Range 2.77416
             Minimum Significant Difference    5.7125


          Means with the same letter are not significantly different.


         Tukey Grouping     Mean   N  Shortcut
                A    293.348  720  2
                B    158.590  720  1

                     The SAS System
8

                    The GLM Procedure

             Tukey's Studentized Range (HSD) Test for WIP

 NOTE: This test controls the Type I experimentwise error rate, but it generally has a higher
Type
                  II error rate than REGWQ.


             Alpha                   0.05
             Error Degrees of Freedom        1429
             Error Mean Square          3052.952
             Critical Value of Studentized Range 3.63754
             Minimum Significant Difference    10.593


          Means with the same letter are not significantly different.


         Tukey Grouping     Mean   N  Scenario
                A    293.574  360  4
                A    293.121  360  2
                B    165.677  360  3
                C    151.504  360  1

                     The SAS System
9

                    The GLM Procedure

           Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP
```

```
NOTE: This test controls the Type I experimentwise error rate.


       Alpha            0.05
       Error Degrees of Freedom   1429
       Error Mean Square    3052.952


Number of Means       2       3       4
Critical Range    9.2202897   9.6622787   10.592928


Means with the same letter are not significantly different.


 REGWQ Grouping     Mean   N  Omega
       A    267.046  360  50
       B    228.877  360  10
       C    204.933  360  1
       C    203.020  360  0.1

            The SAS System
10

           The GLM Procedure

  Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP

NOTE: This test controls the Type I experimentwise error rate.


       Alpha            0.05
       Error Degrees of Freedom   1429
       Error Mean Square    3052.952


    Number of Means       2       3
    Critical Range    6.9963377   8.3677788


 Means with the same letter are not significantly different.


 REGWQ Grouping     Mean   N  Rho
        A    372.840  480  0.85
        B    230.411  480  0.5
        C    74.656  480  0.15

            The SAS System
11

           The GLM Procedure

  Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP
```

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	1429
Error Mean Square	3052.952

Number of Means	2	3
Critical Range	6.9963377	8.3677788

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	ttime
A	229.915	480	15
A	225.725	480	7
A	222.266	480	0

The SAS System

12

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP

NOTE: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	1429
Error Mean Square	3052.952

Number of Means	2
Critical Range	5.7124858

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	Opt_ Criteria
A	229.625	720	2
B	222.313	720	1

The SAS System

13

The GLM Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP

NOTE: This test controls the Type I experimentwise error rate.

```
        Alpha            0.05
        Error Degrees of Freedom   1429
        Error Mean Square    3052.952


         Number of Means       2
         Critical Range    5.7124858


  Means with the same letter are not significantly different.


 REGWQ Grouping     Mean   N  Shortcut
        A    293.348  720  2
        B    158.590  720  1

             The SAS System
14

            The GLM Procedure

   Ryan-Einot-Gabriel-Welsch Multiple Range Test for WIP

 NOTE: This test controls the Type I experimentwise error rate.


        Alpha            0.05
        Error Degrees of Freedom   1429
        Error Mean Square    3052.952


 Number of Means       2       3       4
 Critical Range    9.2202897   9.6622787   10.592928


  Means with the same letter are not significantly different.


 REGWQ Grouping     Mean   N  Scenario
        A    293.574  360  4
        A    293.121  360  2
        B    165.677  360  3
        C    151.504  360  1
```

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