MOBILE ROBOT SIMULATION OF

MID-SIZED HOSPITAL DELIVERY PROCESSESS

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Abstract

Flexible automation in the form of mobile robots holds the potential for decreasing operating costs while improving delivery performance in mid-size hospital delivery systems. This paper discusses the use of simulation modeling to analyze the costs, benefits, and performance tradeoffs related to the installation and use of a fleet of mobile robots within mid-size hospital facilities. The results of this study enable a better understanding of the delivery and transportation requirements of mid-sized hospitals. Specifically, we examine how a fleet of mobile robots can meet the performance requirements of the system while maintaining cost efficiency. We show that for clinical laboratory and pharmaceutical deliveries a fleet of six mobile robots can achieve significant performance gains in terms of turn around time and delivery variability over the current system of three human couriers. Specifically, the simulation results indicate that using mobile robots to perform both clinical laboratory and pharmaceutical deliveries can result in a 75% decrease in cost, a 34% decrease in turn around time, and a 38% decrease in delivery variability.

Introduction

In this study, the University of Virginia's clinical laboratory and pharmacy delivery processes are used as a case study to examine the use of mobile robots within a mid-sized hospital facility. Mid-size hospitals use many different transportation modalities to deliver supplies to and from the service units within a hospital. The University of Virginia Hospital employs human couriers, point-to-point pneumatic tubes, tack-mounted carts, and mobile robotics. This multifaceted transportation system provides a variety of delivery options for the medical staff; however, the current system's over reliance on human couriers for deliveries has inherent disadvantages in terms of cost and delivery reliability. To meet the delivery needs of a hospital, any automated solution will need to handle routine deliveries as well as be flexible enough to handle STAT deliveries or other exceptions to the norm. Flexible automation in the form of mobile robots holds the potential for decreasing operating costs while improving delivery performance. Mobile robots are a specific example of a flexible automatic guided vehicle system. The American National Standard on Industrial Engineering Terminology [1] defines an automatic guided vehicle system (AGVS) as

"A vehicle equipped with automatic guidance equipment, either electromagnetic or optical. Such a vehicle is capable of following prescribed guide paths and may be equipped for vehicle programming and stop selection, blocking, and any other special functions required by the system."

Helpmate Robotics has developed a robotic courier for applications within a hospital environment. The robot is designed to meet a variety of delivery missions in a fully autonomous fashion. The robot is able to make round trip deliveries, one way trips, one-way trips with stops, and rounds with multiple stops. The robot uses a hierarchical control mechanism with a topological map of the hospital embedded into its knowledge base for navigation. Autonomous operation is enabled through the use of multiple sensing modes for including odometer based navigation, sonar, infrared and vision sensors. Additional navigational assistance is also available from specialized reflective tape mounted to the ceiling. A supervisory computer

with radio links to the robots is used in multiple robot applications to prevent deadlock around elevators and in hallways. The robots use specialized algorithms in order to navigate and avoid obstacles within crowded hallways. To allow full access to the hospital, elevator and door actuators must be installed. Typical applications include delivering late meal trays, sterile supplies, medications, specimens and medical records. For more information concerning the capabilities of the robot, we refer the interested reader to Evans [2] and Evans et al. [3].

Automatic guided vehicles (AGV) transport material between pre-specified locations in a facility. They can be used as transporters or they may also serve as a part fixture capable of holding the parts during the processing operation. Fundamentally, an AGV system is specified by:

1. the location of pickup and drop-off points,
2. the path between pickup and drop-off points,
3. the number of vehicles, and
4. the routing and scheduling of vehicles between pickup and drop-off points.

These objectives compete to trade-off cost and system performance in complex ways. Methods that have been used to design and analyze AGV systems include optimization, (Gaskin and Tanchoco [4]), heuristic methods, (Park, Raman, and Shaw [5]), simulation methods, and artificial intelligence methods, (Thesen and Lei [6]). Some authors have considered procedures by which the number of AGVs can be determined. Egbelu [7] proposed four analytical techniques that can be used to determine the number of AGVs required in a particular setting. For example, the CAN-Q method recommended by Tanchoco et al. [8] helps in determining the starting points for the number of vehicles to be used in a simulation experiment. We refer the interested reader to the references for more information on these topics.

Simulation modeling has often been used for automated guided vehicle system design because of its inherent flexibility in modeling the complexity of delivery systems. Ülgen, and Kedia [9] use simulation to design a cellular assembly plant employing AGVs. Prasad and Rangaswami [10] use simulation to analyze

the control systems associated with an AGV system in an integrated circuit board manufacturing application. Newton [11] discusses the use of simulation to determine the appropriate number of AGVs in a manufacturing setting. This research presents the use of simulation to assist in the determination of the appropriate number of AGV's for use in a mid-sized hospital.

This paper first presents an overview of the hospital delivery system under study. We then present a description of the simulation models used to analyze the system. Next, we present the alternatives under consideration, the experimentation process, and the results of the analysis. Finally, we conclude with recommendations and future extensions for this work.

Hospital Delivery System

The University of Virginia is a 683-bed facility. Each floor of the hospital is connected to each other and to the basement by two banks of elevators and via two stairwells. One elevator bank is located on the West Side of the hospital while the other is located on the East Side of the hospital. Each bank of elevators consists of two rows of three elevators each. For each elevator bank, one row of three is reserved for visitors and the other row is reserved for hospital personnel. Figure 1 illustrates the typical layout of a floor within the hospital. The delivery processes for the hospital are arranged according to Figure 2. This study specifically examines the potential use of automation in improving the efficiency of clinical laboratory and pharmaceutical deliveries.

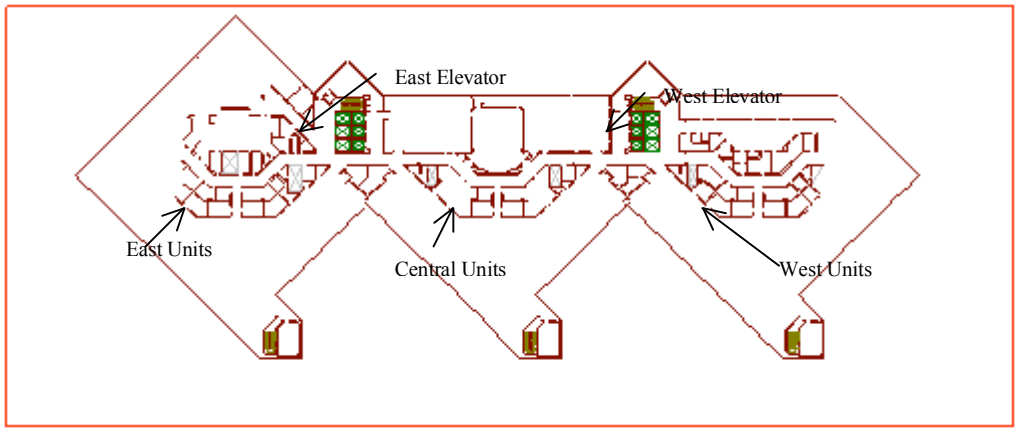

Figure 1: Generic Floor Plan for the 3rd-8th Floors

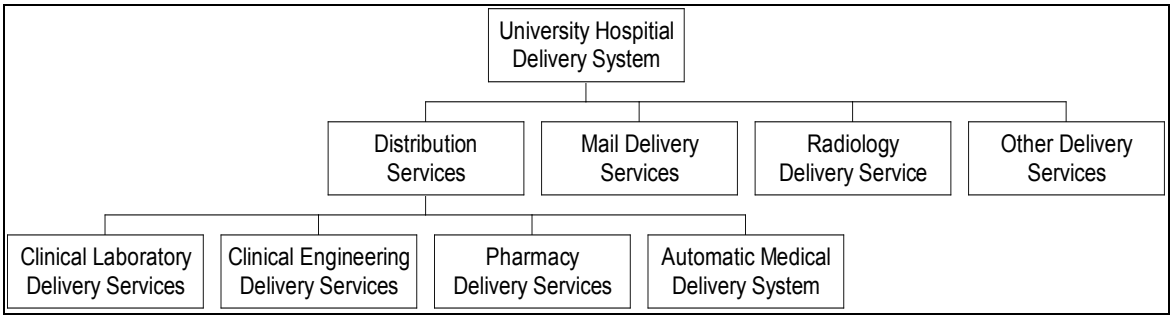

Figure 2: Hospital Delivery System

The clinical laboratory process collects specimens that are placed on floors 3 to 8 from the 29 medical units of the hospital. The clinical laboratory delivery service is divided into STAT and routine deliveries. An activity cycle diagram of this process is presented in Figure 3. For routine pick-ups and deliveries, the courier follows a predefined route. Each courier is assigned two floors: one person for the 3rd and 4th floors, a second person for the 5th and the 6th floors, and a third person for the 7th and 8th floors.

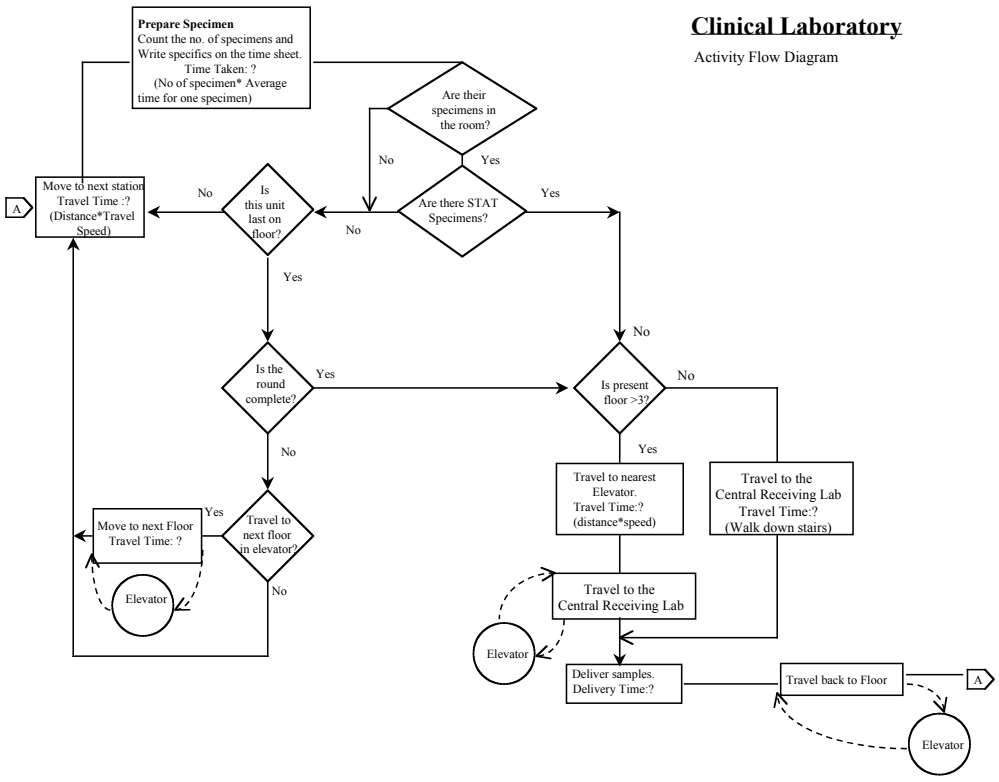

Figure 3: Clinical Laboratory Activity Diagram

Couriers wait in the personnel lounge until it is time to start the shift. At the beginning of the shift, couriers make their way to the top floor of their route and visit each unit assigned to their route on their way to the clinical laboratory. If they have picked up items during the route, they deliver the items to the clinical laboratory; otherwise, they repeat their route. During the shift, there are three breaks that are scheduled for couriers: two breaks of 15 minutes each and 1 break of 30 minutes. If the break occurs, when the courier has items to deliver, the items are first delivered before the break commences. When a specimen requires STAT delivery, the courier picks up the specimen and then takes the best direct route to the clinical laboratory for delivery. Any items that have already been picked up along the route are also dropped off at the laboratory. The courier then travels back to the unit that was next on the route before they responded to the STAT delivery. The determination of whether or not a specimen is STAT is dependent on the nurses or the doctors and their determination of the patients medical needs. No specific STAT delivery time requirement was specified by distribution services although the response should be as immediate as possible and typically less than 15 minutes.

Courier delivery for pharmaceuticals is broken into two distinct delivery processes. These are the delivery of routine pharmacy medicines, and delivery of STAT pharmacy medicines. An activity cycle diagram of routine pharmacy delivery is presented in Figure 4. Three couriers are assigned to deliver medicines to the appropriate units. Couriers performing routine deliveries are each assigned three floors: (3, 4, 5) for one courier and (6, 7, 8) for another courier. STAT delivery to all the floors are carried out by one courier.

Figure 4: Pharmacy Activity Flow Diagram

The delivery process for routine pharmacy is similar to the clinical laboratory delivery process. The courier picks up the medicines at the central pharmacy located in the basement of the hospital and destined for units along their route. The courier uses the elevator to travel to the top floor of the route and then visits each unit on the route. At the nursing station within the unit, a box is kept for pick-ups and deliveries. The courier drops off the medicines at their destinations and picks up any unused medicine for return to the pharmacy. After completing all the floors on the route, the courier returns to the pharmacy to drop off unused medicines and to pick up a new batch of medicines for delivery. Only routine pharmacy delivery is being modeled in this study.

Model Development

The major objective of the simulation models was to develop an understanding of the trade-off between cost and system performance, including utilization of vehicles, amount of work in process, system throughput, delivery turn around time, and delivery variability. This was accomplished by modeling the use of fleets of mobile robots in performing delivery services under realistic hospital demand situations.

To analyze the delivery processes, we developed four models. The first model describes the system as it currently operates using three couriers. The second and third models describe the operation of the system with mobile robots serving as the primary delivery mechanism for the independent operation of clinical laboratory and pharmaceutical deliveries. The mobile robot models act essentially the same as the

courier model except for minor changes to accommodate the speed of the robots, their dwell at the hospital units, and elevator interactions. The fourth model combined the processes associated with clinical laboratory and pharmaceutical deliveries and utilized mobile robots as the delivery mechanism.

Within the models, entities are used to represent: delivery items for clinical laboratory and pharmacy, control logic for the couriers and mobile robots, and logical entities for initializing the model and generating specific arrival processes. We used automated guided vehicle (AGV) movement systems to model the transportation processes associated with both human couriers and mobile robots. See chapter 9 of reference [12] for a complete discussion of modeling AGV systems in simulation. For simplicity, let us refer to the transportation device, either human or robot, as a transporter. We create an entity to control the movement of the transporter. This controller entity follows a process that describes the routes used by couriers or robots within the hospital. Within the movement system, we define the possible paths for the delivery mechanisms between each of the hospital units. These paths include movement between units on the various floors and movement between floors using the elevator. A processing station is associated with each hospital unit. A network of links and intersections describe the paths available to the transporters between the stations. A link describes the path between two intersections. Links can be unidirectional, bi-directional, or spur. Spurs enable the modeling of dead-end links. Intersections are associated with each hospital station and with hallways where multiple links intersect. The elevator travel between floors was modeled with additional links and intersections associated with beginning and ending of an elevator trip.

At the beginning of the simulation, we create a controller entity for each transporter and send the controller entity to the appropriate movement system. A transporter within the movement system picks up the controller entity and then follows the defined route for that transporter. The pseudo-code is illustrated in Figure 5. Figure 6 illustrates the non-stationary arrival pattern for clinical laboratory specimens. Figure 7 presents the probability of requests of delivery for clinical laboratory specimens. The data for these figures was collected over a two-week period. Based on this data, we modeled the generation of entities representing clinical laboratory delivery items according to a non-stationary Poisson process. The demands were generated using a thinning algorithm as specified in Law and Kelton [13, pg. 507-508]. This algorithm

generates demands according to the maximum hourly rate and then thins the demand according to the probability $\lambda_t / \lambda_{max}$, where λ_t is the hourly demand rate for hour t and λ_{max} is the maximum of the for all t. After a demand is generated, the demand is sent to a hospital unit according to the probabilities specified in Figure 7.

Figure 5: Controller Entity Set Up Logic

Figure 6: Clinical Laboratory Non-stationary Arrival Pattern

Figure 7: Clinical Laboratory Hospital Unit Probability of Demand

Items that arrive to a hospital unit for pick-up then wait in a queue associated with the current hospital unit until a transporter (courier or robot) arrives for transport. When the entity controlling the transporter arrives to a hospital unit, it picks up any waiting items from the hospital unit's queue and delays for any material handling required for the items. Each item for pick up is recorded on a transportation sheet. Based on observations, we modeled the pick up time per specimen to be uniformly distributed with a range of 30 to 60 seconds. A robot arriving to a station will announce itself and request that any items be loaded into its cargo hold. If the robot does not get a response, the robot will dwell at the unit for a pre-specified dwell-time. Although the dwell can be caused by the lack of a nurse to load the robot, the dwell can also be triggered by the lack of items for delivery. Since nurses are assigned to the pick-up/drop-off stations, we assume that some nurse will always be available to load the robot and that the dwell is only invoked if no items are needed.

The controller entity then checks to see if any of the picked up items are STAT deliveries. If no STAT deliveries are required, the controller entity continues to the next unit on its route. If any STAT deliveries are present, the controller entity takes the best path to the clinical laboratory for delivery. Based on the demand data supplied by distribution services, the probability of a STAT delivery was approximately

25%. At the clinical laboratory, the controller entity delivers the items and then returns via the best path to the next hospital unit on its route. The controlling entity repeats this process at each hospital unit on its route. Figure 8 illustrates the pseudo-code for the entity as it proceeds through the clinical laboratory delivery process.

Figure 8: Clinical Laboratory Model Logic

Elevators are potential bottlenecks in the delivery process. To model the three elevators reserved for staff use, we considered the entire bank as a resource. Associated with elevator access points on each floor are two stations. An elevator begin-station represents a location where the transporter may seize the elevator before travelling to the next floor. The begin-station also represents a place where the transporter can be positioned to prevent deadlock if another transporter is travelling to the same floor. A courier will experience a delay for the elevator to approximate the resource contention associated with other uses of the elevator. The elevators were observed to obtain the distribution of delay for an elevator after the elevator had been called. The delay data is presented in Figure 9. A best fit of the data indicated that the delay could be modeled with a Gamma distribution. The parameters of the Gamma distribution were obtained by using a statistical best-fit procedure. The best-fit process estimated the parameters as b = 0.575 and a = 2.47 with a squared error of 0.008259. Before traveling to the elevator, the robot will call ahead to the elevator to ensure that no people are using the elevator during its time in the elevator. Because the robot has the ability to call ahead, we assumed that any delay due to other contention for the elevator would be included in the robots travel time to the elevator. An elevator end-station represents the destination of a transporter traveling to a floor via the elevator. This station allows an exit point for the transporter to prevent deadlock and provides a place where the elevator can be released for any other waiting transporters.

Figure 9 Elevator Delay Distribution

When traveling within the hospital, couriers do not block each other's paths. To model this situation using AGV constructs, the couriers were modeled as zero length transporters. This allows passing on the links and mitigates any need for deadlock avoidance or zone control. When travelling, the mobile robots contend for space within the hallways. Two robots should not be permitted to travel down a bi-directional hallway, and a distance of approximately 2 meters should be maintained between the robots. This situation is handled via the use of zone control, properly directed links, and the allocation of waiting zones (such as the elevator begin and end stations). See reference [12] for more information on these constructs. Because routes are defined to cover a subset of floors, two robots will never be on the same floor at the same time except when visiting the clinical laboratory. Figure 10 illustrates the paths on the second floor to avoid deadlock.

Figure 10 Hospital Second Floor

Orders for pharmaceutical products arrive to the pharmacy from the hospital units through the Hospital Information System. These orders are generally placed by doctors. The central pharmacy keeps records of the number of items that were requested and the time they were requested by the units. From this data, we tabulated the number of items requested at each unit during each hour of the day. This yields a measure of the demand for drop-offs. Figure 11 illustrates an aggregate of the demand across the day for all units and indicates that the demand varies significantly with the time of day. Figure 12 illustrates the percentage of overall daily demand generated by each individual unit. Similar to the clinical laboratory demand generation process, we modeled the demand process for the pharmacy with a non-stationary Poisson process with the arrival rate varying by the hour of the day. Time spent by couriers delivering pharmaceutical articles during their visit to the hospital unit is around 30 seconds and it is relatively independent of the number of pharmaceutical products that are dropped. We modeled the time spent dropping off specimens to be uniformly distributed with a range of 30 to 60 seconds.

Figure 11 Pharmacy Non-stationary Arrival Pattern

Figure 12 Hospital Unit Probability of Demand for Pharmacy Articles

The items arrive to the central pharmacy for pick-up then wait in a queue associated for a particular hospital unit until a transporter (courier or robot) arrives for transport. When the entity controlling the transporter arrives to a hospital unit, it searches for any articles that need to be dropped off at the Hospital Unit and delays for any material handling required for the items. If the robot does not have anything to drop off, the robot will dwell at the unit for a pre-specified period-of-time. The entity repeats this process at each hospital unit on the route. After servicing the last unit on the route, the transporter (courier or robot) travels back to the central pharmacy to repeat the rounds.

Model Verification and Validation

Verification is concerned with building the model right. It is used in the comparison of the conceptual model to the computer representation. The input parameters and logical structure of the model have to be correctly represented. The verification procedure for our model followed a questions/answer format.

1. Has someone other than the developers checked the computerized representation of the model?

2. Has a flow chart of each logical possible action a system can take when an event occurs been made?

3. Was the animation of the computerized model examined for logic inconsistencies?

4. Has the output parameters of the model been verified by someone other than the model developers?

5. Was debugging and model tracing performed?

In each case, the answer was in the affirmative. For example, we validated the cycle times generated from the model by discussing the outputs with a supervisor in Distribution Services. Cycle time is the time required to complete one round that starts from the first unit and ends at the first unit. Cycle time

includes the time taken to drop-off items at the central laboratory. The staff of Distribution Services estimates the cycle time for the clinical laboratory routes to be between 20 and 30 minutes. To confirm this estimate, we ran our simulation model of the current system under varying demand conditions and estimated the average cycle time for the routes. The results from Table 1 indicate that the cycle time is dependent upon the demand rate, but that the values roughly confirm the intuitive analysis of the staff. We also walked the route to confirm the times estimated from the model. The difference can be attributed to the fact that our model does not account for unscheduled breaks taken by the couriers.

Table 1 Average Cycle Time

Validation is concerned with building the right model. It is utilized to determine that a model is an accurate representation of the real system. Validation is usually achieved through an iterative process and by determining the discrepancies and the insight gained to improve the model. Validation is the overall process of comparing the model and its behavior to the real system. For the validation procedure, we are using a widely followed approach formulated by Naylor and Finger [14]. Our main emphasis was to validate with the hospital administration the structural and data assumptions of our model. In addition, we examined the sensitivity of our model to variations in the model inputs.

To analyze the sensitivity of the input parameters we performed a 2^k factorial experimental analysis on the courier and robot models. We investigated the effect of varying the arrival generation rate, the elevator delay distribution, the STAT/regular specimen distribution and the dwell time of the robots at the hospital units. Arrival generation rate is the observed daily aggregate of specimens that are generated by the units of the hospital. Elevator Delay is the time delay a courier experiences after the courier calls an elevator and its subsequent arrival from any floor. Elevator delay was varied by changing the delay parameter by a factor of 10% above and below the nominal. Specimen Distribution is defined as the percent of STAT and Regular specimens for the total specimens that are generated in one day. This distribution was

changed by a factor of 10% above and below the nominal level to obtain the two levels for this factor. Dwell Time is defined as the time spent by the Helpmate Robot at the units for pickup before it is noticed and specimens loaded. The dwell time can be adjusted during installation for the robots. Table 2 summarizes the factors used to perform experimental design and their levels. Each design point was replicated 20 times. The response variables examined were the turn-around time, the delivery variability, the cycle time, and the utilization.

Table 2 Factors and Levels

As to be expected, the ANOVA tests indicated that one-way, two-way, and three-way interactions were all significant for the factors. In addition, as indicated in Table 3, the change in response variables behaved as expected for the selected range of inputs. Similar results were found for the robot model and its factors. We refer the interested reader to Kumar [15] for a complete description and analysis of the experiments. These results clearly show that the model is well behaved over the range of input factors and that subsequent analysis can be performed using the nominal levels of the factors.

Table 3 One-Way Terms for Courier Model Factorial Design

Trade-off Analysis

Trade-off analysis involves determining multiple criteria for decision making and the formation of a decision function that yields an objective value for the best alternative. In this study, we made a comparison between the existing system with three couriers and mobile robot alternatives using 2, 3, and 6 robots. While more sophisticated multiple criteria decision making formulations exist, we developed a simple

additive objective function to incorporate each of the competing objectives. Our results will indicate that a more sophisticated analysis is probably not warranted in the case. The performance metrics of interest were:

1. Cost: Cost is defined as the equivalent annualized cost of the alternatives over a 5 year planning horizon using a 6% discount rate.

2. Turn-Around-Time (TAT): Turn around time is defined as the time lapsed between the generation of the specimen and its subsequent delivery to the Clinical Laboratories.

3. Delivery Variability (DV): Delivery variability is defined as the standard deviation of the turn around time. Delivery variability gives an indication of the consistency of the delivery process.

4. Cycle Time (CT): Cycle time is the time taken by the courier or the robot to complete one round of the assigned route. Cycle time takes into account the time that is spent delivering both STAT and regular specimens.

5. Utilization (UTIL): Utilization is defined as the ratio of the total time spent by a courier or a robot carrying specimens to the total available time for delivery.

The objective function incorporates each of the indices of performance. Each index of performance is weighted by the decision-maker, to describe the importance the decision-maker gives to the objective. After evaluating the objective function for each alternative, we can then decide which alternative is better. The objective function is defined as follows:

$$IP = \sum_{i=1}^{5} w_i IP_i$$

where IP_i is the Index of Performance for the ith objective and w_i is the corresponding weight that the decision-maker attaches to each index of performance. The weights must sum to one. Since the indices of performance in the objective function have different units of measure, a linear scaling method was used to

convert the observed average values into comparable units of measure. The linear scaling method scales the individual observed values to a scale of 0-100, where 100 is mapped to a high value and 0 corresponds to a low value.

Clinical Laboratory Modeling Results

Table 4 summarizes the comparison obtained for the alternative delivery mechanism in the hospital. The table presents the values obtained from the simulation model for each of the robot and courier models averaged across 50 replications under the nominal parameter settings. The standard deviations for those performance measures estimated from the simulation are given in parenthesis.

Table 4 Clinical Laboratory Summary of Performance Measures

The salaries paid to the couriers are the primary factor in the courier system. The robotic cost analysis must take into consideration such factors as installation cost and accessory equipment. For example, the following is a summary of the information obtained for the three robot cost analysis.

1) Robot Support Equipment Requirement:
    a) Annunciators 17
    b) Door Sensors 1
    c) Door Sensors and actuators 1
2) Robot Requirement:
    a) Number of Robots 3
    b) Number of Backpacks 3
    c) Number of Radios 2
3) Cost of Robot

a) Cost of Equipment $301,800

b) Cost of Installation $ 37,100

c) Annual Service Contract $ 24,114

4) Cost of Courier Service $407,613

The cost of the courier system is based on a loaded hourly rate of $10.26/hr for 24 hours/day and 365 days/year. In order to obtain full yearly coverage over sick days, vacations, etc. 1 person is considered equivalent to 1.4 FTE.

To perform sensitivity analysis on the objective function, the weights associated with each IP must be varied over a range of values. Since cost and turn around time tend to be the most important performance measures, we varied the weights on these responses and fixed the weights for the other performance measures. This also allows for a simpler but still insightful analysis. Table 5 presents the three weighting schemas used in our analysis. Weighting schema 1 places the highest importance on cost and low importance on turn around time. Weighting schema 2 places equal weighting between cost and turn around time. Weighting schema 3 places the highest importance on turn around time and lowest importance on cost. Figure 13 presents the values obtained for the objective function for the alternatives under the weighing schemas. A one to one replacement of the couriers has the potential to reduce the cost by 74% with an increase of 20% delivery time. The six-robot alternative dominates the other alternatives by maintaining low cost and significantly improving the turn-around-time and delivery variability.

Table 5 Weighting Schemas

Figure 13 Objective Function Values for Clinical Laboratory Deliveries

Pharmacy Modeling Results

To analyze the pharmacy delivery process, we developed two models. The first model describes the system as it currently operates using two couriers. The second model describes the operation of the system with mobile robots serving as the primary delivery mechanism. Table 6 presents the summary of the pharmacy results for the performance measures. Figure 14 shows the trade-off in the objective function across the alternatives. Projected cost savings of 37% are derived by the implementation of the 3-robot alternative; however, the 3-robot alternative has a 27% increase in turn around time.

Table 6 Pharmacy Model Summary Results

Figure 14 Objective Function Values for Pharmacy Deliveries

Combined Model Results

To analyze the combined delivery process, we developed a model for 6-robots delivering pharmaceutical articles and clinical laboratory articles. Table 7 presents the summary values and Figure 15 presents the objective function values under various weighing schemas.

Table 7 Pharmacy Model Summary Results

Figure 15 Objective Function values for Combined Deliveries

For the combined model, robots perform both pharmacy and clinical laboratory delivery. The combined delivery had a 75% decrease in cost, a 34% decrease in turn around time, a 38% decrease in delivery variability while virtually matching the cycle time and utilization performance of the courier based system.

Summary and Conclusions

This study analyzed the costs, benefits and performance issues related to the installation and use of a fleet of mobile robots within a mid-sized hospital. Simulation models were developed and tested for clinical laboratory and pharmacy deliveries. Simulation modeling enabled the hospital delivery system to be realistically modeled so that system performance could be predicted under the alternatives of 2, 3 and 6 robots. From the modeling results, it is clear that a 6-robot alternative dominates the other alternatives by maintaining low cost and significantly improving the turn-around time and delivery variability.

The results of this project indicate that mobile robots are highly suitable for automating the delivery mechanisms of mid-sized hospitals. The ultimate success of such a system depends on the proper training and acceptance of the hospital staff. As with many automation projects, change management issues should receive high priority during implementation so that the full benefits and acceptance of the system can be realized. Our future research areas include the study of the reliability of the system. For example, we are currently investigating the affect that the deployment of the robots will have on the hospital elevator system. Specifically, we are interested in issues involved with the unavailability of the elevators and with robot downtime. We are investigating these and other factors within the context of an analytical hierarchical process methodology.

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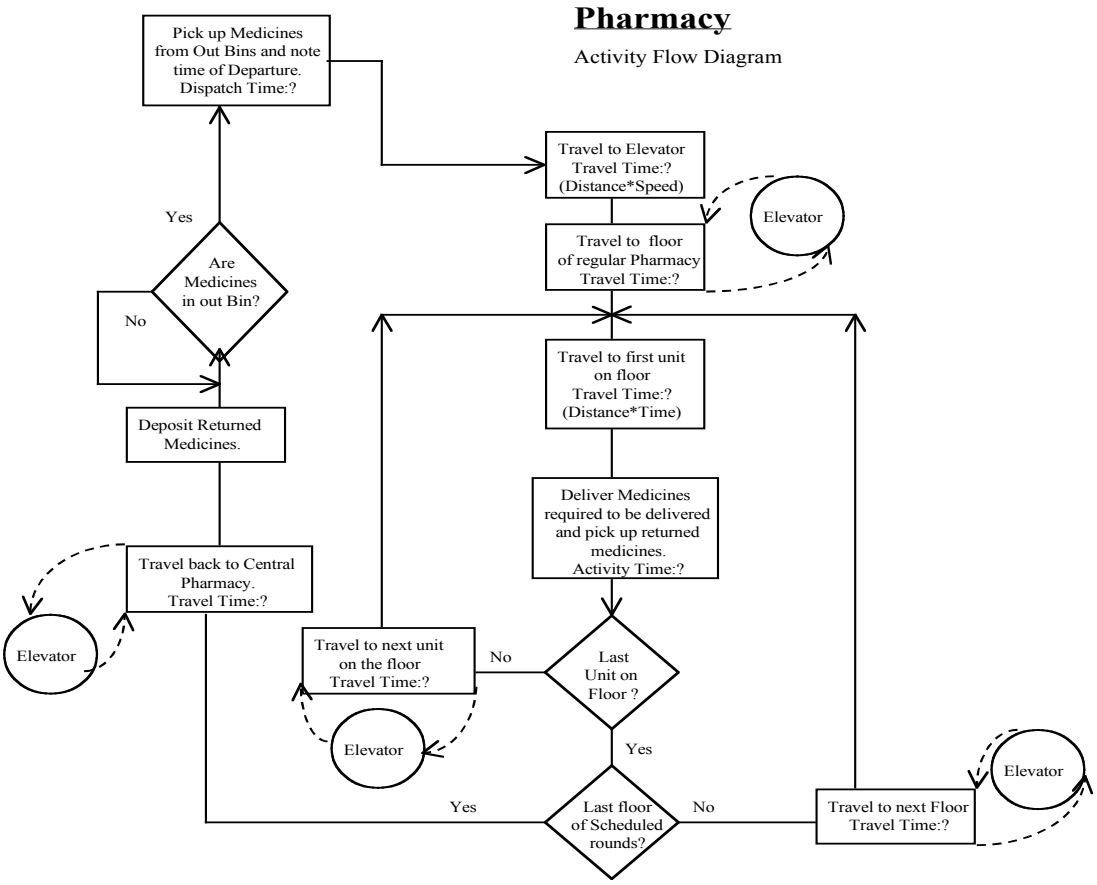

Figure 4: Pharmacy Activity Flow Diagram

For each transporter in the model, create a controller entity
Send to Controller Setup Station
At Controller Setup Station
If controller entity is courier type
    Request a courier transporter
Else
    Request a mobile robot transporter
Assign first unit destination
Assign elevator for travel to first unit's floor
Assign closest beginning elevator station
Assign ending elevator station
Transport to first unit on route

Figure 5: Controller Entity Set Up Logic

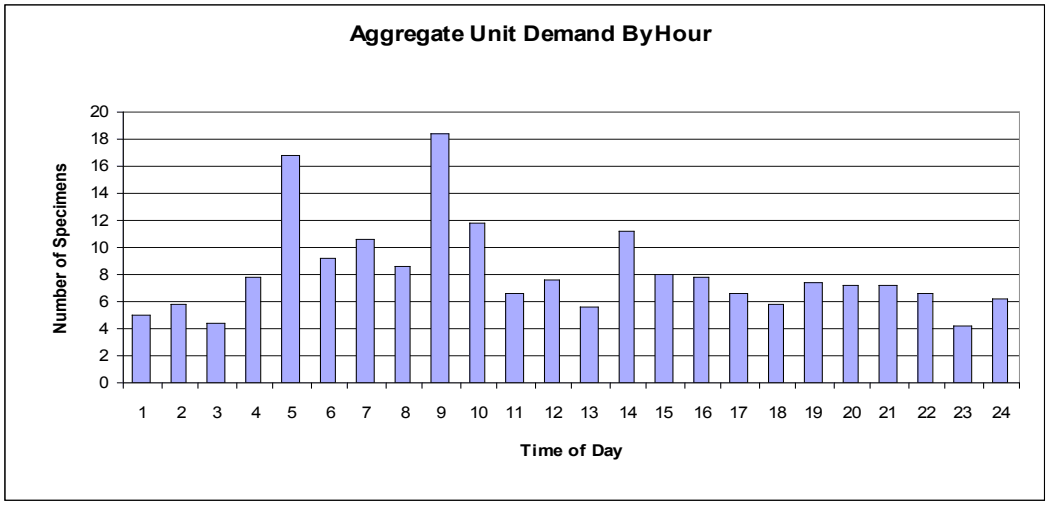

Figure 6: Clinical Laboratory Non-stationary Arrival Pattern

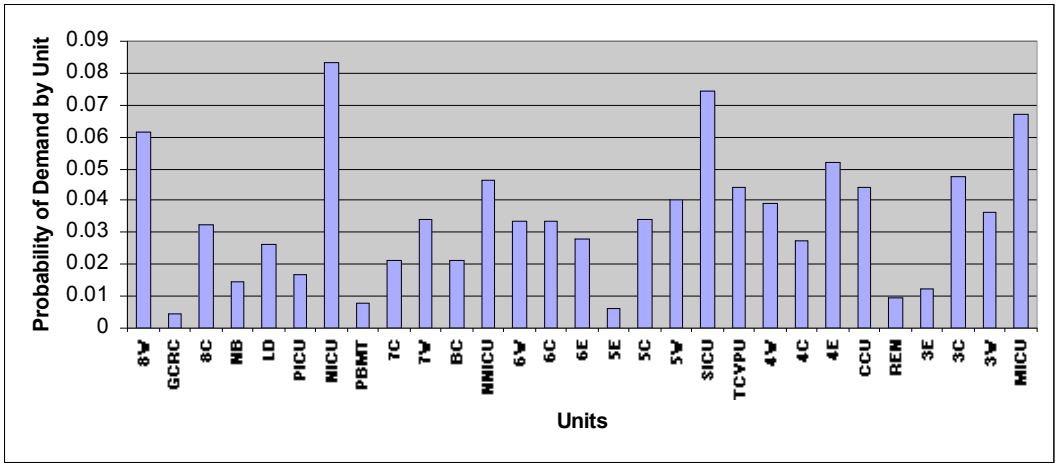

Figure 7: Clinical Laboratory Hospital Unit Probability of Demand

```
At a hospital unit
If first unit on route, mark time for cycle time collection
    Assign current unit
    Assign current unit's nearest elevator
    Assign current unit's nearest elevator station
If no items to pick up
    Delay for dwell time  /* Zero delay for courier */
While items remain to be picked up
    Pick up 1 item
    Seize loading device
    Delay for load time
    Release loading device
    Update number of items on transporter
    Update amount of space available on transporter
End While
If any items were picked up
    If an item was of type STAT or at last unit on route
        Make elevator assignments
        Transport to clinical labs
    If next unit is on different floor
        Make elevator assignments
    Transport to next unit
Else
    If break time, take break
    If next unit is on different floor
        Make elevator assignments
    If last unit on route
        Transport to first unit
    Else
        Transport to next unit
```

Figure 8: Clinical Laboratory Model Logic

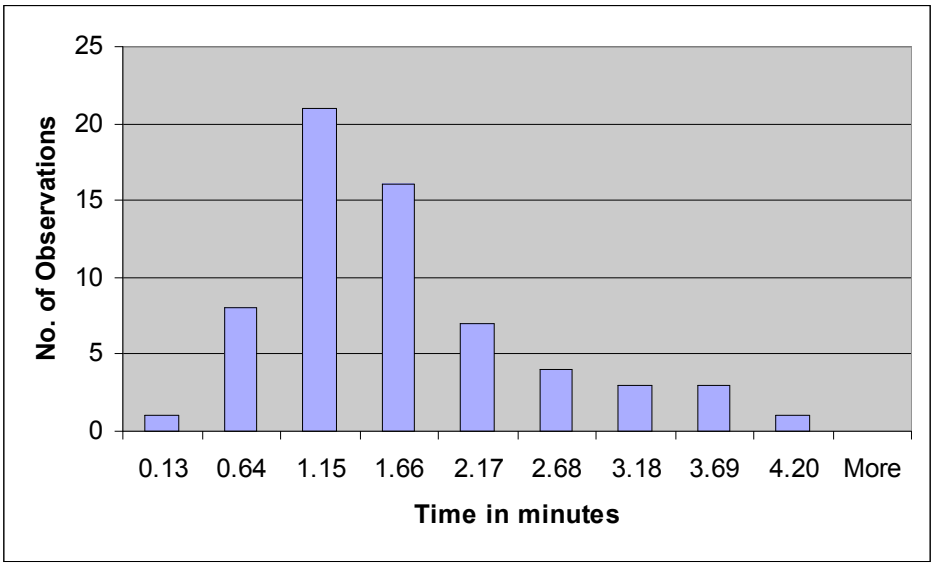

Figure 9 Elevator Delay Distribution

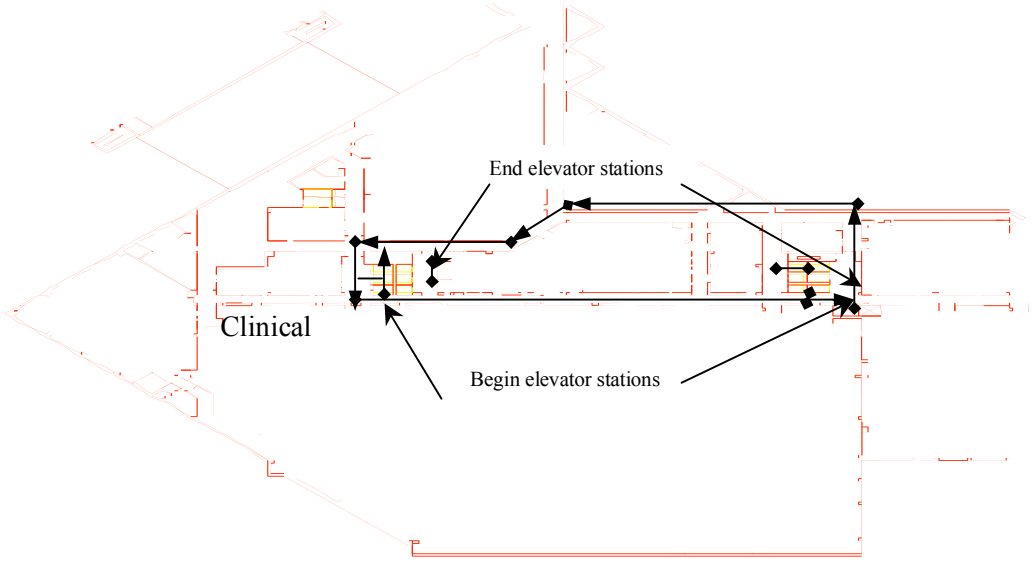

Figure 10: Hospital Second Floor

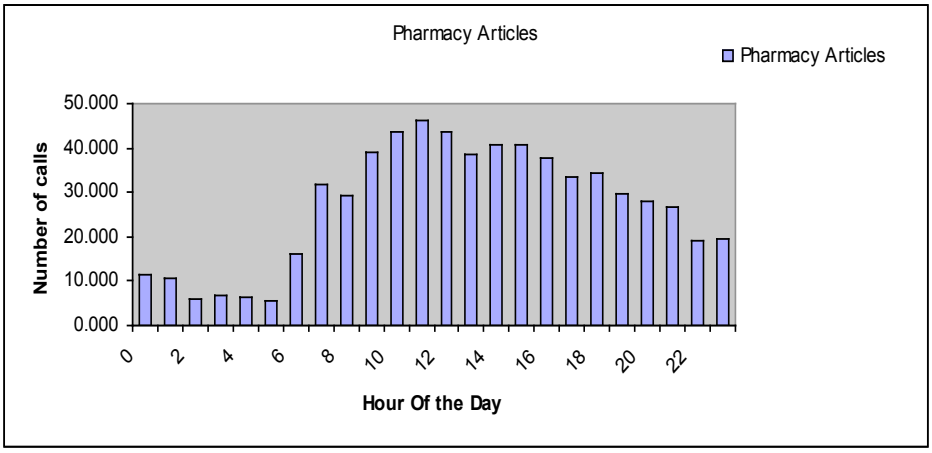

Figure 11: Pharmacy Non-stationary Arrival Pattern

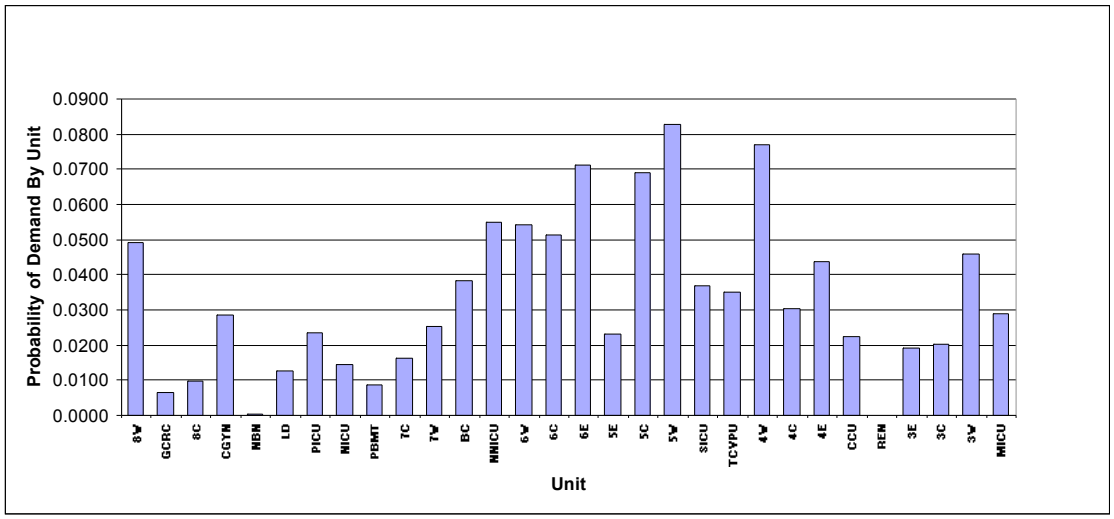

Figure 12: Hospital Unit Probability of Demand for Pharmacy Articles

Table 1: Average Cycle Time

Low Demand	15.01
Medium Demand	18.32
High Demand	20.91

Table 2: Factors and Levels

	Levels	
Factors	**Low**	**High**
Generation rates	400 Specimens/day	800 Specimens/day
Elevator Delay (courier model only)	Gamma(0.575,2.45)*0.9	Gamma(0.575,2.45)*1.1
Dwell Time (robot model only)	30 seconds	2 minutes
Specimen Distribution	15% STAT vs. 85% Regular	35% STAT vs. 65% Regular

Table 3: One-Way Terms for Courier Model Factorial Design

	TAT		DV		CT		UTIL	
Term	**Coeff.**	**Std Dev**	**Coef**	**Std Dev**	**Coef**	**Std Dev**	**Coef**	**Std Dev**
Constant	28.74	0.21	20.30	0.25	26.68	0.19	87.69	0.097
Generation Rate	4.29	0.21	3.77	0.25	4.20	0.19	1.78	0.097
Elevator Delay	1.89	0.21	1.57	0.25	1.79	0.19	0.50	0.097

Table 4 Clinical Laboratory Summary of Performance Measures

	Two Robots	Three Robots	Six Robots	Courier
COST	$81,110	$107,605	$178,027	$407,614
TAT (min.)	47.28 (1.97)	33.54 (1.07)	18.9 (0.44)	16)
DV (min.)	24.77 (1.87)	16.67 (0.82)	8.63 (0.04)	20.72 (2.83)
CT (min.)	67.03 (2.01)	42.25 (0.87)	20.72 (0.33)	26.3 (1.57)
UTIL	92.50% (0.44)	91.90% (0.63)	81.70% (1.52)	88.33% (0.68)

Factors
1-Specimen Generation
2- Elevator Delay
3-Specimen Dist.

Table 5: Weighting Schemas

	Cost w_1	TAT w_2	DV w_3	CT w_4	UTIL w_5
$\vec{w}_1$	0.65	0.05	0.10	0.10	0.10
$\vec{w}_2$	0.35	0.35	0.10	0.10	0.10
$\vec{w}_3$	0.05	0.65	0.10	0.10	0.10

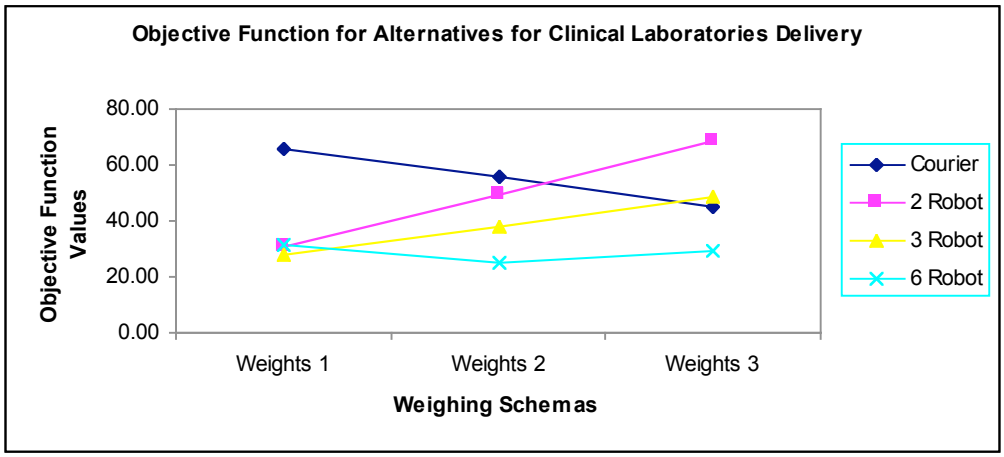

Figure 13 Objective Function Values for Clinical Laboratory Deliveries

Table 6 Pharmacy Model Summary Results

	Alternatives		
Performance Index	**2 Robots**	**3 Robots**	**Courier**
Cost	$86,141.00	$104,579	$281,742
Turn Around Time	102.25	71.16 min.	55.87
	(15.06)	(13.25)	(9.21)
Delivery Variability	86.88	57.87 min.	49.22
	(22.97)	(19.724)	(13.86)
Average Cycle Time	57.37	42.35 min.	30.86
	(2.11)	(1.255)	(1.11)
Utilization	13.28%	56.87%	11.69%
	(3.22)	(7.323)	(1.97)

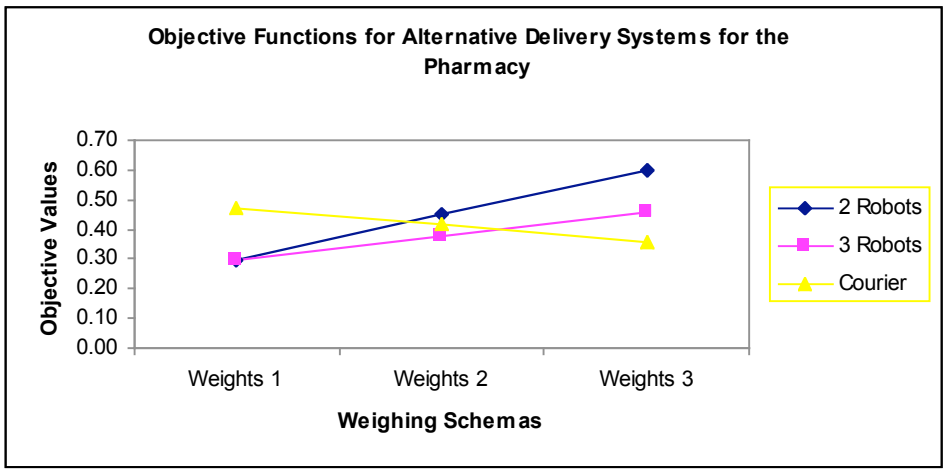

Figure 14 Objective Function Values for Pharmacy Deliveries

Table 7: Summary for Combined Delivery

	Results In Absolute Terms	
Performance Index	6 Robots	Courier
Cost	$178,076	$689,356
Turn Around Time	28.14 (1.461)	42.69 (5.055)
Delivery Variability	12.30 (1.404)	20.01 (2.963)
Average Cycle Time	28.97 (0.722)	28.70 (0.937)
Utilization	89.69% (0.508)	86.72% (1.031)

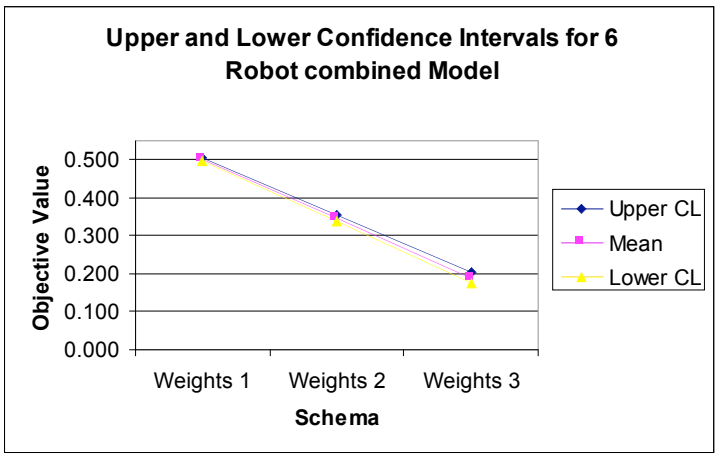

Figure 15 Objective Function values for Combined Deliveries