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Thesis

Modeling Fabrication of Nuclear Components
An Integrative Approach

Los Alamos
NATIONAL LABORATORY

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Modeling Fabrication of Nuclear Components An Integrative Approach

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Research in an area such as facility layout and its application to a complex problem such as the casting operation where there are many possible paths to follow requires attention to crucial issues. I wish to express my sincerest gratitude to Dr. Paul Finch for providing the focus, direction, and patience in guiding me through my research. My thanks are also extended to Dr. Dave Olivas for the countless hours of discussion, meetings, and review of results. Dr. Ram Prasad introduced me to a new realm of problem-solving techniques. He provided me with the background to pursue many interesting projects; for his time and interest in my ventures, I am appreciative. I thank Dr. Satish Kamat, Dr. Mary Anne Staffeldt, and Dr. Teresa Cremers for generously providing their time to serve on my graduate committe.

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PUBLICATIONS

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

MODELING FABRICATION OF NUCLEAR COMPONENTS:

AN INTEGRATIVE APPROACH

BY

KAREN WELLS HENCH

ABSTRACT

Reduction of the nuclear weapons stockpile and the general downsizing of the nuclear weapons complex has presented challenges for Los Alamos. One is to design an optimized fabrication facility to manufacture nuclear weapon primary components in an environment of intense regulation and shrinking budgets. This dissertation presents an integrative two-stage approach to modeling the casting operation for fabrication of nuclear weapon primary components. The first stage optimizes personnel radiation exposure for the casting operation layout by modeling the operation as a facility layout problem formulated as a quadratic assignment problem. The solution procedure uses an evolutionary heuristic technique. The best solutions to the layout problem are used as input to the second stage - a simulation model that assesses the impact of competing layouts on operational performance. The focus of the simulation model is to determine the layout that minimizes personnel radiation exposures and nuclear material movement, and maximizes the utilization of capacity for finished units.

Chapter 1

INTRODUCTION

1.1 Background

The end of the Cold War has dramatically changed the role of the nuclear-weapon stockpile and the associated research, development, and testing of weapons by the national laboratories. Formerly, nuclear deterrence was achieved by large-scale production and a commensurate large-scale budget. The Strategic Arms Reduction Treaty (START) and START II called for reducing the strategic-weapons arsenals of the United States and the former Soviet Union. The existing, reassembled, or retrofitted weapons in the enduring stockpile will be stored indefinitely to ensure nuclear competency. The streamlined weapons complex of the future will focus on long-term storage of nuclear material, weapons dismantlement, and a modest fabrication and rebuild capability of weapons components as a hedge against aging or degraded weapons in the stockpile. The Department of Energy (DOE) has been tasked with ensuring the continued safety and reliability of the weapons stockpile through the auspices of the Stockpile Stewardship and Management Program [47]. This program will administer the activities related to the research, design, development, and testing of nuclear weapons and the production and maintenance of the weapons stockpile.

The Plutonium Facility (TA-55) at Los Alamos National Laboratory (LANL) is currently the only operating facility in the nation with established R&D programs that can be implemented on a larger scale to provide production capability for the fabrication and recovery of plutonium. Ancillary activities such as waste recovery and disposal, non-destructive assay, analytical chemistry, radiography, and transportation also currently exist at LANL. Assuming a fixed lifetime in years for the nuclear portion of a weapon, a specific number of weapons will have to be requalified/reused or manufactured annually to maintain the weapon stockpile. The challenge for TA-55 is to design an optimized manufacturing facility that is capable of producing the needed quantity of nuclear weapon primary components (pits) subject to the constraints imposed by oversight organizations and funding sources. Reconfiguring the existing pit fabrication area at TA-55 to accomodate the proposed level of production is estimated to cost $50M. This figure includes the decontamination and disposal of outdated equipment, installation of new gloveboxes and equipment, and upgrade of existing gloveboxes.

Historically, the location of gloveboxes in a processing area has been determined without benefit of industrial engineering studies to ascertain the optimal arrangement. The opportunity exists for substantial cost savings and increased process efficiency through careful study and optimization of the proposed layout by constructing a computer model of the fabrication process. This dissertation presents an integrative approach to modeling a nuclear primary component fabrication operation using a mathematical technique for the formulation of the facility layout problem and a simulation model to evaluate the impact that alternative layouts have on performance measures.

1.2 Problem Definition

The existing pit fabrication area is located in one wing of TA-55, and occupies an area on the order of 20,000 square feet. Operations located in the area are casting, machining, non-destructive assay, assembly, inspection, and testing. The operations are in fixed locations within the wing; however, individual processes within the operations can be relocated to minimize exposure to technicians and to increase operational efficiency.

The casting operation is performed in the foundry, and it is the operation considered to present the highest radiation exposure hazard to radiation workers. The processes located within the foundry have the most flexibility for relocation (at a cost) with respect to the rest of the pit fabrication operations. All other factors being equal (complexity of material flows, skill level of personnel, working hours, waste generation, and interim storage), the casting operation represents the worst case of the pit fabrication operations. The casting operation will be modeled, and the analysis techniques developed can then be applied to the remainder of the operations.

The foundry consists of two glovebox lines connected by a single trolley system. Each glovebox line is divided into two trunklines, each with its own material transport device. There are 17 possible locations on the glovebox lines to which 16 casting operations can be assigned. The conceptual arrangement of glovebox locations within the foundry is shown in Figure 1.1.

1.3 Research Objectives

The goal of modeling the casting operation is to produce an optimal layout configuration for the foundry. A configuration can be defined as a matching of a fixed number of processes to an equal number of locations within the foundry. The estimation of personnel radiation exposures at a given capacity is of primary importance. An optimal configuration will best utilize the resources available to maximize capacity and reduce personnel exposures. An additional objective is the determination of an optimal operating strategy for the casting operation. Factors influencing an operating policy include the number of radiation workers that are required, the need for additional processing and transportation equipment, and the need for additional storage.

Modeling the fabrication and recovery processes to determine the optimal layout and operating strategy can best be accomplished in two stages. The first stage is to model the layout of the facility as a quadratic assignment problem and apply an optimization technique. The optimization model is well suited to determining alternative layouts that optimize personnel radiation exposure. The second stage is to construct a simulation of the casting operation using the best layout solutions from the optimization model in the first stage as inputs. The objective of the simulation

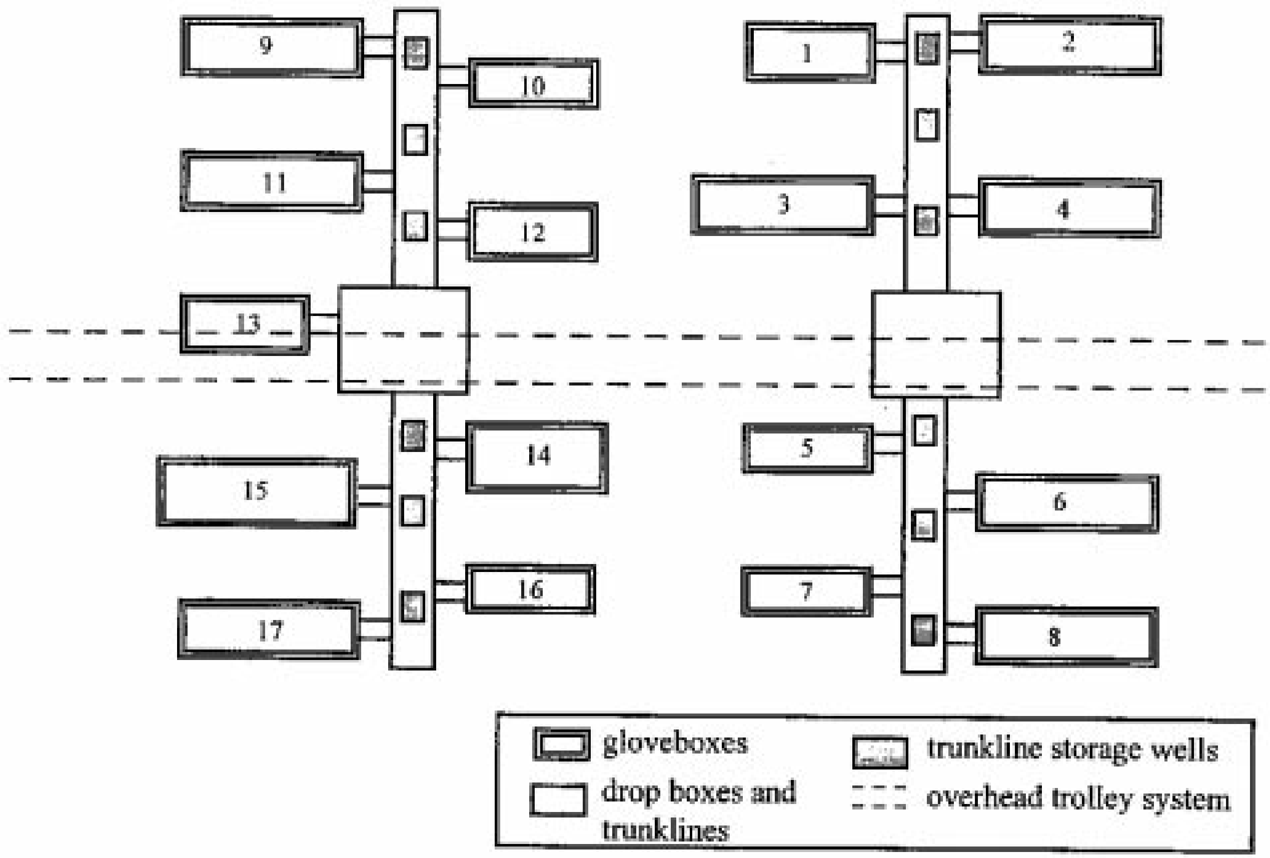

Figure 1.1 Arrangement of 17 gloveboxes in the foundry

model is to determine the layout that minimizes personnel radiation exposures and nuclear material movement, and maximizes capacity.

1.4 Summary of Contributions

Simulation is the most commonly used method for studying the complex interactions of operators, materials, and equipment in a stochastic environment. Simulation allows an experimenter to estimate the performance of a system under competing configurations in order to determine which combination of parameters results in an optimal operating policy. However, using a simulation model alone to simultaneously evaluate the performance of a complex system and optimize the operating parameters is not practical because of the number of parameters. Optimization of process parameters and analysis of a system operating under those parameters are two very different problems, each with their own formulations, data requirements, and constraints. A better approach is to employ a methodology that combines an optimization technique yielding [intelligent] solutions for input to a simulation model that, subsequently, estimates the performance of the system being studied. By iteratively generating a set of parameters and then studying the effect on system response, the optimal operating strategy can be determined. The framework for the modeling process is illustrated in Figure 1.2.

Our simulation results demonstrate the effectiveness (and feasibility) of applying an integrative approach to modeling exposures and material flow through the foundry. The optimization model produces a set of good layout configurations

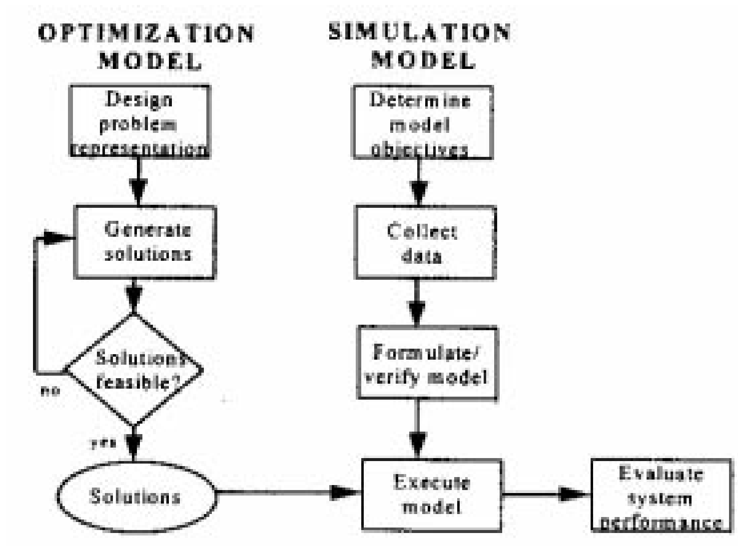

Figure 1.2 Framework for the modeling process

with only five seconds of execution time. Constructing a similar set of layout solutions by hand would require an enormous amount of time. Each solution is presented to the simulation model which produces data on capacity, radiation exposures, utilization, and bottlenecks. Analysis of simulation model results reveals the best arrangement of processes in the casting operation when all the factors are considered. The methodology can be extended to any operation where process location is integral to efficient use of resources and communication between processes or facilities.

1.5 Organization of the Dissertation

Chapter 2 presents a tutorial on criticality and radiation safety which are significant factors in handling nuclear material and integral components in the design of both models. Chapter 3 is devoted to the discussion of the quadratic assignment problem and its applicability to facility layout. This chapter details previous research into the assignment of facilities to locations and concludes with the specific formulation for the casting operation. Chapter 4 presents a literature survey of the fundamental components of genetic algorithms (GAs) and their use as a solution methodology for the quadratic assignment. The specific approach used in this dissertation is also discussed in this chapter. Chapter 5 outlines the structure of the simulation and the statistical analyses that are performed on the performance measures. Chapter 6 presents the results of the two models. The efficacy of the genetic algorithm in producing feasible solutions is illustrated. Finally, the results of the simulation model that incorporates the top 10 solutions are presented. Conclusions about the feasibility and effectiveness of the dual-model approach are contained in Chapter 7 as well as a discussion of future research.

Chapter 2

CRITICALITY AND RADIATION SAFETY

2.1 Structure of the Atom

The three primary particles of an atom are protons, neutrons, and electrons. A proton is located in the nucleus and is a positively charged particle. The number of protons in the nucleus determines the element. An electron is a negatively charged element that orbits the nucleus of an atom and determines an element s chemical properties. Ions of an element have either a positive or negative charge depending on the number of protons and electrons in the atom. The neutron, also located in the nucleus, has no electrical charge. Atoms of the same element, which have a different number of neutrons, are called isotopes. Isotopes have the same chemical properties; however, the nuclear properties can be very different. For instance, some isotopes are inherently unstable due to the number of neutrons in the nucleus. In the process of trying to become stable, these atoms emit energy (radiation) in the form of alpha particles, beta particles, neutrons, and gamma or x-rays (see Figure 2.1).[1] Ionization occurs when electrons are removed from a neutral atom by radiation with sufficient energy to remove an electron from its orbit around the atom. Plutonium and uranium, two of the elements that are commonly processed at TA-55, both emit ionizing

[1] Illustrations in Figures 2.1, 2.2, and 2.3 are provided courtesy of Jim Mahan and Tammy Tucker, Los Alamos National Laboratory [33].

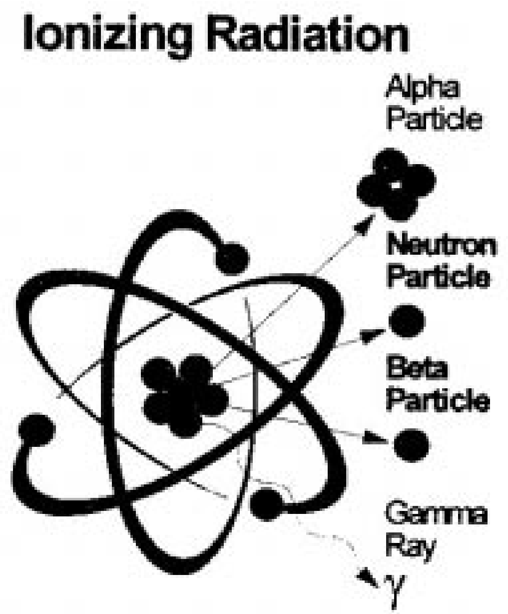

Figure 2.1 Ionizing radiation

radiation and require special handling precautions and procedures to mitigate hazards to radiation workers.

2.2 Biological Hazards of Radiation

Radiation causes damage to human tissue through ionization of the atoms in the cells. The extent of the cellular damage depends on whether the nucleus or cytoplasm is struck; an insult to the nucleus of a cell may damage the DNA. Ionizing radiation can also cause chemical reactions at the cellular level that may adversely affect tissues or organs. Actively dividing cells such as those found in the bone marrow, intestinal tract, hair follicles, and reproductive organs are more sensitive to radiation damage than brain or muscle cells.

There are four consequences of exposure to ionizing radiation, depending on the length and the amount of exposure: (1) no cellular damage occurs, (2) chromosomal damage occurs and is repaired by the cell, (3) chromosomal damage occurs and the cell ceases to function properly, or (4) the cell dies. An acute whole-body radiation dose results from a large exposure in a short period of time. Usually the dose is overwhelming to the body, and it cannot repair itself. Symptoms may include reduced blood count, hair loss, nausea, or in extreme circumstances, death. A chronic radiation dose occurs in small quantities over a long period of time. An example of this is naturally occuring background radiation such as cosmic radiation, terrestrial radiation, and radon. Biological effects from a chronic radiation dose include somatic effects such as cancer and genetic effects.

To minimize the biological effects of chronic radiation to individuals working with nuclear materials, administrative limits for occupational doses havc been established. A dose is defined as the amount of energy per unit mass deposited in a volume of tissue [6]. The radiation dose unit is rad (radiation absorbed dose) which only accounts for the amount of radiation that is absorbed and not the type of radiation. A quality factor applied to the measurement provides an equivalent measure that accounts for differences in types of radiation and the energy level of the radiation. The roentgen equivalent man or radiation equivalent in man (rem) is the unit for measuring radiation exposure to personnel. This measure takes into account energy absorbed by the body and the potential biological effect caused by different types of radiation. For example, the absorbed dose for an equal amount of energy from gamma ray radiation and low-energy neutron radiation may each be 1 rad; however, the gamma ray dose equivalent is 1 rem, and the neutron dose equivalent is 10 rem. The Department of Energy (DOE) occupational dose limit for a radiological worker is 2 rem/year. The TA-55 administrative control limit for the pit fabrication area is 1.5 rem/year. Doses exceeding these levels do not necessarily result in biological damage to an individual; these limits are strictly administrative goals.

2.3 Criticality

Isotopes such as ^{239}Pu, ^{241}Pu, ^{235}U, and ^{233}U are termed fissile materials. These isotopes have the capability of undergoing a fission process where the nucleus of the atom is struck by a neutron and the neutron is absorbed. The nucleus breaks into two smaller parts, and a tremendous amount of gamma radiation is released. The fission produces two or three neutrons which strike other atoms. If sufficient fissile material (critical mass) is present, the fission process continues and results in a chain reaction. If the chain reaction eventually dissipates, because not every fission results in another, it is termed subcritical. If every fission results in one other fission, the reaction is critical. If every fission results in multiple fissions, the reaction is supercritical.

A criticality event can release enough thermal energy to boil solutions, melt metals, or cause explosions and fire. More importantly, the short-duration (milliseconds) burst of neutrons and gamma rays is lethal to personnel in the immediate vicinity. Proper handling and storage of nuclear material is essential to prevent the occurrence of a criticality incident. The primary mechanism for preventing a criticality accident is to engineer containers, tanks, transportation devices, and storage facilities to reduce the chances nuclear material interaction. Operationally, administrative controls limit the amount of nuclear material that is permitted in a container, glovebox, transport device, or storage location [32].

Criticality safety limits are provided to radiological workers for any location where fissile material could be present. These limits are specific to the form of material and the location. The simulation model incorporates criticality limits by not allowing a quantity of nuclear material that would exceed the limits to be present in any location. For example, material transport devices can convey only one container of nuclear material, and cannot deliver material to a location where nuclear material is present.

2.4 Radiation Safety

The four basic types of ionizing radiation of concern at TA-55 are alpha particles, beta particles, gamma or x-rays, and neutrons. Each type has distinct physical characteristics, range, biological hazards, and safety precautions (see Figures 2.2 and 2.3). An alpha particle consists of 2 protons, 2 neutrons, and no electrons. The positive charge of the particle causes it to ionize adjacent electrons and release a large amount of energy in a distance of 1 to 2 inches. Alpha particles are not an external radiation hazard, because they can be stopped by the epidermis. However, if an alpha particle is inhaled or ingested, it becomes an internal source of exposure and can cause extensive damage to body tissue. Precautions taken to prevent exposure

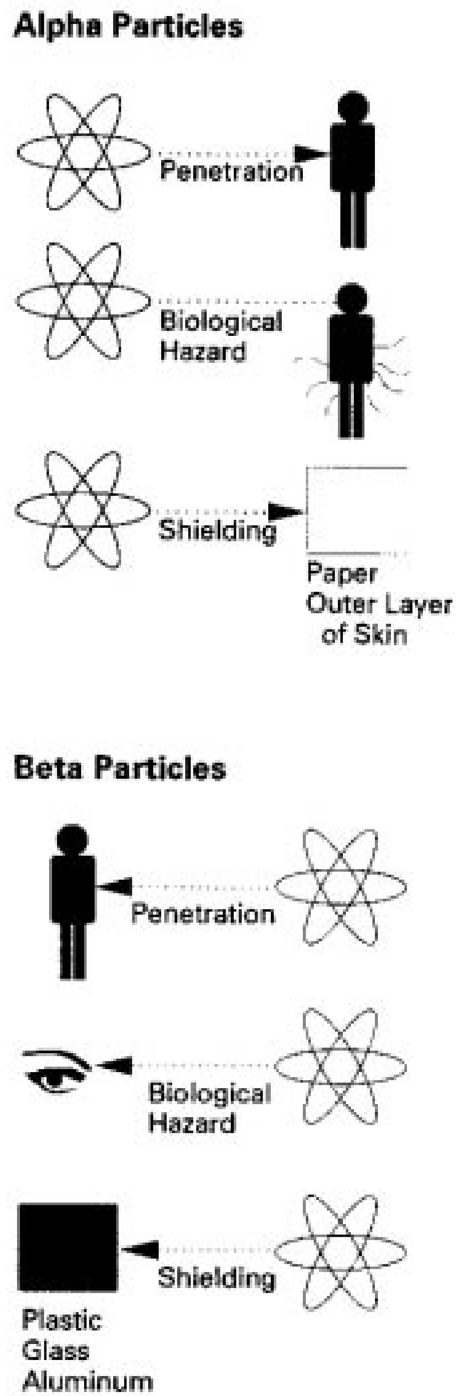

Figure 2.2 Characteristics of alpha and beta particles

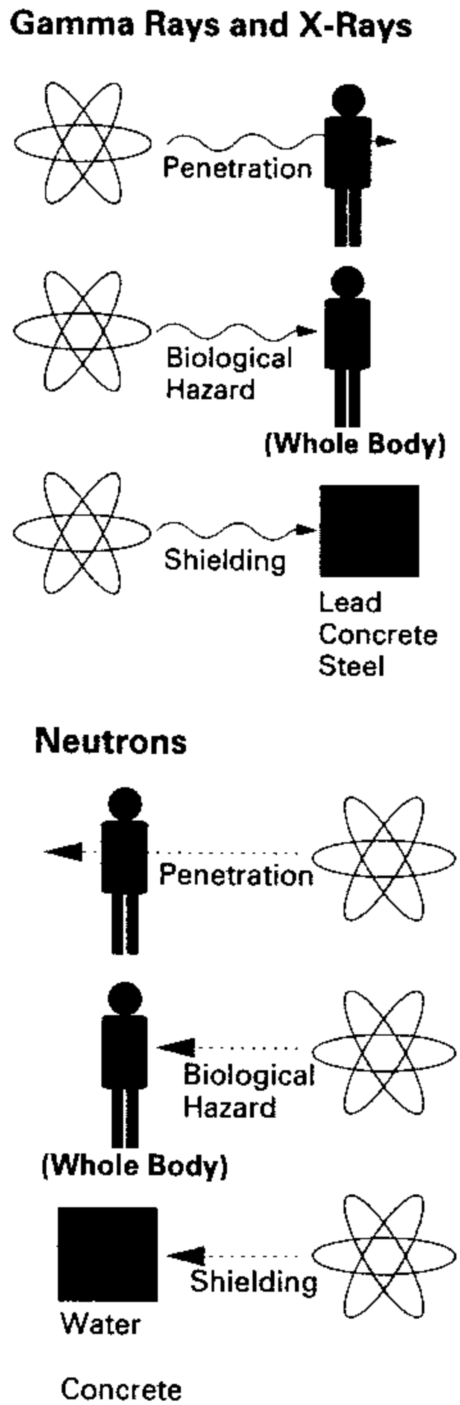

Figure 2.3 Characteristics of gamma rays and neutrons

to alpha particles include protective clothing, respirators, and material handling in a contained environment.

The beta particle is negatively charged and is emitted from the nucleus of an atom. It is physically identical to an electron and results in ionization of adjacent atoms due to the repulsive forces between the beta particle and the electron. The beta particle has a limited penetrating ability of about 10 feet in air. This particle is an external hazard to the skin and eyes, and becomes an internal hazard if ingested or inhaled. An additional precaution to prevent exposure to beta particles is wearing specialized safety glasses.

Gamma and x-rays are similar, in that both types of radiation are electromagnetic waves with no electrical charge. Ionization occurs as a direct result of interaction with electrons in adjacent atoms. Gamma/x-ray radiation can travel several hundred feet in air, because it possesses no mass and the energy is transmitted to its target. Proximity to a gamma/x-ray source results in whole-body exposure to an individual. Shielding the source with dense materials like lead or steel is one effective mechanism for minimizing exposure. Another is minimizing the time spent near the source and/or maximizing the distance from the source.

Neutron radiation results when neutrons are ejected from the nucleus of an atom. A collision between a neutron and the nucleus of another atom is a direct interaction; indirect interaction occurs when a charged particle or other ionizing radiation is released during direct interaction. This can cause ionization in human tissue. Neutrons have a high penetrating ability in air (several hundred feet), similar to gamma rays. Shielding against neutron radiation is best accomplished by using moderating materials with a high hydrogen content such as water, polyethylene, concrete, or neutron absorbing materials such as boron.

The primary objective of the optimization and simulation models is to produce a layout of the foundry area that minimizes exposure that radiation workers receive from radioactive material contained in the gloveboxes and storage wells. This is accomplished by maximizing the distance between high-exposure processes or those processes with a relatively large amount of radiation worker attention time and minimizing the time the workers handle the material. The simulation model tracks material movement and handling time which aids in the comparison of layout configurations. Material located in storage wells significantly contributes to the background radiation in the processing area. The simulation also attempts to minimize interim storage in these wells. The objective of minimizing exposures to radiological workers is in direct conflict with the objective of maximizing throughput. Therefore, the throughput for a layout where exposures are minimized indicates the capacity of the system and not the maximum throughput.

Chapter 3

FACILITY LAYOUT AS A QUADRATIC ASSIGNMENT PROBLEM

3.1 Facility Layout Problem

The importance of the physical layout and design of a manufacturing process cannot be underestimated. The efficiency of an operation depends on the proper utilization of personnel and equipment, and the efficient movement and storage of materials. Traditionally, facility layout has been accomplished manually by employing a cut-and-paste approach [49] where permutations of a layout are explored by rearranging work stations and equipment. This approach is effective when the number of locations is small. However, the number of alternative arrangements is n!, where n = the number of available sites to locate a facility, department, workstation, or piece of equipment, and if n = 17, the number of potential layouts is in excess of 350 trillion. Clearly, the trial and error approach is not feasible for determining the best solution.

Buffa [7] introduced a graphical approach to the facility layout problem (FLP) that considers work flow between departments and attempts to locate those departments in proximity to where the flow is relatively large. Muther [36] developed another graphical approach called Systematic Layout Planning (SLP) that incorporates subjective inter-departmental relationships through the use of a closeness rating system. The limitations of the graphical approaches as the problem size increases led to the development of a multitude of computer applications for generating and evaluating alternative facility layouts. Most of the computer-based facility-layout techniques can be categorized as either quantitative, qualitative, or multi-criteria methods.

3.1.1 Quantitative Methods

Koopmans and Beckman [26] were the first researchers to model the facility layout problem as a Quadratic Assignment Problem (QAP), a well-known classical combinatorial optimization problem. The problem involves the assignment of n distinct facilities to n fixed locations to minimize the total material handling cost or flow between the facilities. Facilities, locations, and material flow are loosely defined to meet the context of the particular problem application. A formulation of the problem by Lawler [29] is

$$\min \quad \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} \sum_{l=1}^{n} b_{ijkl} x_{ij} x_{kl} \tag{3.1}$$

$$b_{ijkl} = \begin{cases} f_{ik} c_{jl} + a_{ij} & \text{if } i = k \text{ and } j = l, \\ f_{ik} c_{jl} & \text{if } i \neq k \text{ or } j \neq l, \end{cases} \tag{3.2}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} x_{ij} = 1, \quad \forall i, \tag{3.3}$$

$$\sum_{i=1}^{n} x_{ij} = 1, \quad \forall j, \tag{3.4}$$

$$x_{ij} \in \{0,1\}, \quad \forall i, j, \tag{3.5}$$

where,

a_{ij} = fixed cost of locating facility i at location j ,
f_{ik} = flow of material (interaction) between facilities i and k, and
c_{jl} = cost of transporting material between locations j and l.

Quadratic assignment formulations for the FLP vary according to the particular application. These formulations may include distances between facilities, revenue (loss) from operating a facility in a particular location, identical flows between facilities, and cyclic operations. Bazaraa [2] and Hillier and Connors [20] represented the FLP using a quadratic set covering problem (QSP) by dividing the area under study into contiguous blocks and assigning facilities to the blocks.

In addition to the QAP and QSP, there are numerous formulations of the FLP using linear integer and mixed-integer programming [4,8,24,27,34]. Lawler [29] formulated his approach to QAP using an equivalent integer programming problem. By defining $y_{ijkl} = x_{ij}\, x_{kl}$, (3.6)
where x_{ij} and x_{kl} are defined in Eqs. (3.3) - (3.5) the objective function becomes:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} \sum_{l=1}^{n} b_{ijkl}\, y_{ijkl}, \tag{3.7}$$

where,

$$b_{ijkl} = \begin{cases} f_{ik} c_{jl} + a_{ij} & \text{if } i = k \text{ and } j = l, \\ f_{ik} c_{jl} & \text{if } i \neq k \text{ or } j \neq l, \end{cases} \tag{3.2}$$

$$\text{s.t.} \quad \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} \sum_{l=1}^{n} y_{ijkl} = n^2, \tag{3.8}$$

$$x_{ij} + x_{kl} - 2y_{ijkl} \geq 0 \quad \forall\, i,j,k,l, \tag{3.9}$$

$$y_{ijkl} \in \{0,1\}, \quad \forall\, i,j,k,l, \tag{3.10}$$

where,

a_{ij} = fixed cost of locating facility i at location j,
f_{ik} = flow of material (interaction) between facilities i and k, and
c_{jl} = cost of transporting material between locations j and l.

The above formulations assume that the number of facilities and locations are equal, and that each facility will be assigned a location, or alternatively, each location will have an assigned facility. If the number of locations is greater than the number of facilities, inequalities can be introduced into the equations or dummy facilities can be added.

Lawler s formulation of the QAP has n2 xij variables and 2n constraints. His equivalent integer programming formulation has n2 xij variables, n4 yijkl variables, and n4 + 2n + 1 constraints, as documented in Kusiak and Heragu [27]. An integer programming formulation of the QAP used by Love and Wong [34] where locations are specified by rectangular coordinates has n2 xij variables and n2 + 3n constraints. Computational experience with the Love and Wong formulation indicates that the approach is not appropriate for problems with more than eight facilities [27]. A mixed-integer linear programming reformulation for the QAP was proposed by Kettani and Oral [25]. Their approach linearizes the quadratic objective function and reduces the number of 0-1 integer variables. Results indicate that the reformulation can accomodate a problem size of N=15 with two hours of CPU time required to produce a solution.

Solution procedures for the FLP can be divided into two categories - optimal and heuristic [39]. Two classes of the optimal algorithms are branch-and-bound and cutting-plane. Examples of branch-and-bound techniques are those developed by Lawler [29] and Kaku and Thompson [23]. Cutting-planes algorithms were developed by Bazaraa and Sherali [4] and Burkard and Bonniger [9].

The QAP is a difficult combinatorial optimization problem belonging to the class of NP-complete problems [17] which means that no deterministic algorithm has been found to yield an optimal solution in a reasonable amount of time. Primary disadvantages of optimal algorithms are their computational complexity and computer memory requirements [8]; optimal algorithms have proven to be practical for only QAP problems on the order of 15 to 20 [35] . The intractability of many problems led to the investigation of heuristic algorithms for the solution of the QAP. Heuristic approaches vary widely according to the application and author. Many approaches are problem-specific; others are robust and applicable to a wide variety of problems. Among the most significant contributors in the field are Hillier and Connors [20], Heragu and Kusiak [19], Burkard and Bonniger [9], Armour and Buffa [1], Bazarra and Kirca [3], and Vollman et al. [50]. Kusiak and Heragu [27] present a detailed review of both optimal and heuristic approaches to the QAP.

The most successful heuristics are those that yield near-optimal solutions and avoid getting stuck in local optima. Traditionally, heuristic procedures were divided into two main classes: construction and improvement. Construction algorithms involve a serial assignment of each facility to a location until a solution is built. This process is the basis for construction algorithms developed by Hillier and Connors [20], Lee and Moore [30], Seehof and Evans [43], and Scriabin and Vergin [42]. Improvement algorithms use an initial solution to perform systematic pairwise or three-way exchanges between facilities until the best solution is obtained. This process generates a solution that depends on the initial solution and the procedure may get caught in local optima. An improvement algorithm is the basis for the best known and most widely used facility layout program, Coordinate Relative Allocation of Facilities Technique (CRAFT) developed by Armour and Buffa [1] and Buffa [7].

A new class of algorithms experimentally proven to be effective at solving difficult combinatorial problems is termed evolutionary heuristics [35]. This class includes Boltzmann Machine, Evolution Strategy, Genetic Algorithms, MultiGreedy, Sampling and Clustering, Simulated Annealing, Tabu Search, and Immune Networks. These algorithms iterate to a sub-optimal solution given an initial, randomly chosen solution or population of solutions. These heuristics use a limited amount of computing time and memory relative to other traditional techniques and have been used to solve larger problems.

3.1.2 Qualitative Methods

The primary difficulty with a quantitative approach to solving the FLP is the assumption that the objective function is unidimensional which often requires that costs must be assigned to intangible goals. Decision analysis of alternative layouts is frequently performed in the context of conflicting requirements and regulations, limited resources, and inadequate data. Quantitative approaches do not consider qualitative interrelationships between operations. However, qualitative factors influencing a layout decision are subjective and often conflicting. Without a systematic approach to the analysis, inaccuracy and inconsistency in the decision process results [44].

Qualitative techniques are based on Muther s SLP system that assigns subjective closeness ratings in the analysis of the problem. Qualititative factors that commonly influence the assignment of facilities (or departments, etc.) to locations are safety considerations, operating environment (noise, temperature, humidity, etc.), flexibility, and aesthetics [39,44]. The closeness ratings are expressed in the following manner when values are assigned to the factors [36,49]:

A	Absolutely necessary
E	Especially important
I	Important
O	Ordinary
U	Unimportant
X	Undesirable

Once values are assigned to the ratings, qualitative routines attempt to produce arrangements where facilities are located together when proximity is important, and apart when distance is desirable. A commonly used program that establishes the interrelationships between facilities and makes assignments based on the closeness ratings in Computerized Relationship Layout Planning (CORELAP) [30]. This program selects the facility (department, etc.) with the highest rating and places it in the center of the layout. Subsequent facilities are added to the layout based on the relationships with the already assigned layouts.

3.1.3 Multi-Criteria Methods

In most facility layout problems, the analytical methodologies for generating an optimal or near-optimal solution are well researched and documented. However, in practice, many nonquantifiable issues exist for which a quantitative technique is not applicable. Conversely, most decisions regarding competing layout alternatives cannot be based solely on qualitative aspects of the problem without considering quantitative work-flow volume. An integrated approach combining the techniques for both quantitative and qualitative analyses is appropriate.

Several authors have developed multi-criteria models [22, 38, 39, 40, 44, 45, 49] for the generation and evaluation of alternative facility layouts. Butler et al. [10] used a quadratic integer goal programming model to determine configuration of services and bed allocation in a hospital setting. Their model incorporates Lee s preemptive goal programming where a hierarchy of priority levels is established for multiple goals [31].

Urban [49] demonstrated how to implement a multi-criteria model using existing software (CRAFT) to solve the QAP by modifying the cost term. In Lawler s formulation, the cost term bijkl of Eq. (3.2) is redefined when a closeness rating and a rating factor are incorporated into the work-flow volume:

$$b_{ijkl} = \begin{cases} (f_{ik} + wr_{ik})c_{jl} + a_{ij} & \text{if } i = k \text{ and } j = l, \\ (f_{ik} + wr_{ik})c_{jl} & \text{if } i \neq k \text{ or } j \neq 1, \end{cases} \qquad (3.11)$$

where,

r_{ik} = departmental interrelationship closeness rating, and

w = nonnegative weight reflecting importance of rating and work flow volume.

Work-flow volume is determined as usual. Urban assigned the closeness values in the following manner: A=4, E=3, I=2, O=1, U=0, and X=-1. He suggested that assigning a negative value to facilities with X closeness ratings provided better separation in the final layout. The weighting factor is extremely important when the qualitative costs are incorporated into the work-flow volume. If the weights of the closeness ratings are too small, the quantitative aspects of the cost function dominate. If the weights are too large, the qualitative aspects of the problem overwhelm the quantitative ones. Experimentation is often required to determine the appropriate values for the weights. Urban [48,49] illustrated that a facility layout optimization model using multiple objectives is possible and practical for a variety of applications.

3.2 The Quadratic Assignment Formulation for the Foundry

The purpose of modeling the foundry as a QAP is to assign processes to glovebox locations with the objective of minimizing exposures to radiation workers. By separating high-radiation and/or high attention time processes, the background contribution to the overall radiation exposure is reduced. The quadratic assignment formulation for the foundry in Eq. (3.12) is a compact form of Eq. (3.1). The coefficient, bijkl, is modified to reflect radiation dose as the flow of material or interaction between processes. The cost associated with locating a process at a particular location in the foundry is computed as the summation of radiation exposures from each process i and the contribution of background exposure from each process k adjacent to process i. Traditionally distance is an attenuating factor in the cost calculation; here, it is a reducing factor in that the cost term is inversely proportional to the square of the distance. The omission of the integer variables, xij and xkl, in the formulation are a result of location assignments provided by the GA solution. The solution accounts for the cross products xijxkl that have a value of 1. The cross products that equal 0 do not enter into the calculation. In the objective function, the fixed cost of assigning a process to a location is not considered. A cost value based on the process-to-location assignment is computed separately and reported.

$$\min \quad \sum_{i=1}^{nprocs} \sum_{k=1}^{nprocs} \left(\frac{d_i \, at_k \, c}{dist^2(a_i, a_k)} \right) \tag{3.12}$$

where,
nprocs = number of processes in the casting operation,
d_i = radiation dose rate from process i received by worker at process k (mRem/hr),
at_k = worker attended service time for process k (hours),
c = constant capacity of foundry,
(a_i, a_k) = assigned location of processes i and k, and
$dist^2\ (a_i, a_k)$ = the distance (squared) between locations (ft^2).

The following assumptions are used in the foundry QAP: (1) all gloveboxes are fully loaded with nuclear material at all times, (2) radiation dose rates and attention times are specific to each process, and (3) distances between glovebox locations are fixed and are process independent.

Chapter 4

GENETIC ALGORITHMS AND THE OPTIMIZATION MODEL

4.1 Genetic Algorithms and Optimization

The term genetic algorithm suggests a family of parallel, randomized-search optimization heuristics that employ the mechanics of natural selection and natural genetics to evolve an optimal solution from a population of initial feasible solutions [21]. The QAP is a difficult combinatorial problem that is known to be NP-complete [17]. Many heuristic and enumerative schemes have been applied to the QAP with limited success. Enumerative algorithms investigate the search space by evaluating an objective function at every point in space; however, these search techniques are unsuitable for large problems due to dimensionality concerns. Intuitively, random search procedures that search the solution space and save the best solutions are an improvement over enumerative schemes, but in practice, they too suffer from lack of efficiency. Evolutionary techniques such as tabu search and genetic algorithms have proven to be very effective in solving non-convex optimization problems [11,13, 46] where determining the quality of solutions is possible, but iterative generation of improved solutions is difficult using deterministic methods. Of the two methods, genetic algorithms produce more diverse solutions because multiple points in the solution space are simultaneously explored. The purpose of the optimization model is to produce a set of diverse solutions that can be examined by the simulation model.

Genetic algorithms differ from traditional optimization procedures in the three ways [18]:

1. GAs use a coding of the parameter set to randomly perform an exploitive search of a solution space.
2. A search is conducted simultaneously on a population of points, not a single point.
3. The quality of a solution is determined directly by evaluating an objective function.

Clarification is needed on the goals of optimization before examining the fundamentals of GAs and their implementation to the optimization of a facility layout problem. Traditional solution procedures seek optimization through convergence to an optimal point. Calculus-based procedures generate local optima in often noisy search spaces. Enumerative schemes seek optimal solutions, but are hampered by the complexity of a problem. Complex systems often require satisficing or compromising optimality for improvement. The facility layout problem lends itself to performance improvement where the solution obtained may be be competitive but sub-optimal.

4.2 Genetic Algorithm Terminology

The terminology used to describe GA structure and operators is borrowed from the biological paradigm of natural selection first specified by Holland [21]. GAs share common features in generating solutions [46]:

1. A set of feasible solutions, or population.
2. A process where parents are chosen from a population to breed and produce offspring (reproduction).
3. A method where new solutions are obtained by recombining features from multiple previous solutions (crossover).
4. A method where new solutions are obtained by randomly permuting previous solutions (mutation).
5. Selection of individuals from the population with the best objective function values (fitness evaluation).
6. Removal of individuals from the population (culling).

The primary data structure for a GA is the chromosome or string representation of a single solution. Each decision variable within the chromosome, or decision vector, is referred to as a gene; the value of a gene is called an allele. The approaches to initializing populations, reproduction, crossover and mutation, selection, and culling are as numerous as the researchers in the field. The encoding scheme used to represent solutions, to a large extent, determines the approach used. Genetic operators such as crossover and mutation operate on the encoding of the solutions and not the solutions themselves. This distinction profoundly affects the success of a GA application, because cleverly designed problem-specific encoding schemes reduce the search space and aid in the efficiency in generating new solutions.

Fit chromosomes exhibit similarities between them. If a causal relationship exists between the similarities and the fitness, this information can be exploited to guide a directed search for improvement [18]. These similarities, called schemata, refer to a subset of chromosomes with common genes at certain positions. A schema is a pattern of genes that is matched between chromosomes. A schema has properties of defining length and order that differentiate schemata. The defining length, denoted by $\delta(H)$ where H is the schema, is the distance between the first and last specific gene in the chromosome. The order, denoted by $o(H)$, is the number of specific positions of genes in the chromosome. For example (using a binary encoding scheme for a chromosome), one schema is 011*1*0 and a second schema is 1*1**** where "*" is interpreted as don t care about value. The first schema has a defining length, $\delta(H)$, of 6 and an order, $o(H)$, of 5; the second schema properties are 2 and 2 respectively. The Schema Theorem [18] or the Fundamental Theorem of Genetic Algorithms [21] states that above-average schemata receive exponentially increasing trials in subsequent generations. Shorter schema have a better chance of surviving to the next generation, and are more desirable. The expected number of a particular schema H in the next generation under reproduction, crossover, and mutation, is given by

$$m(H,t+1) \geq m(H,t) \cdot \frac{f(H)}{\bar{f}} \left[1 - p_c \frac{\delta(H)}{l-1} - o(H) p_m \right] \tag{4.1}$$

$m(H,t), m(H,t+1)$ = the numbers of schema in population at time t and $t+1$, respectively,

$f(H)$ = the average fitness of the chromosomes representing schema H at time t,

$\bar{f}$ = the average fitness of the entire population,

p_c = the probability of crossover, and

p_m = the probability of mutation.

4.3 Random Keys

The application of a genetic algorithm to QAP begins with the development of a chromosomal representation for the candidate solutions. The genetic algorithm generates offspring by applying recombination and mutation operators to the encoded solutions; however, use of a traditional operator may result in an infeasible solution.

As an illustration, consider two permutations of a literal encoding of an assignment of facilities to locations. In Parent A, for example, facility 1 is assigned to location 1, facility 2 is assigned to location 4, facility 3 is assigned to location 3, etc. A crossover site at position 3 has been randomly chosen.

Parent A: 1 4 3 | 6 2 5

Parent B: 1 3 2 | 4 6 5

The resulting offspring is:

Offspring A: 1 4 3 4 6 5

Offspring B: 1 3 2 6 2 5

Neither offspring is a valid solution because of the omission of one facility and the duplication of another in each. Many authors have developed problem-specific recombination operators which overcome the solution feasibility problem. Bean [5] and Norman and Bean [37] proposed a method of chromosomal encoding that does not require a specialized representation for each problem variation. Random keys is an algorithm specifically developed to address sequencing and optimization problems such as multiple machine scheduling, vehicle routing, resource allocation, and the quadratic assignment problem. Bean s approach has shown encouraging results for these classes of problems.

The fundamental difference between the random keys approach and other techniques is the encoding of solutions using random uniform (0,1) variates. The values of the keys are used to decode solutions. All genetic operations are performed on the keys. The genetic algorithm searches the random variate space and not the literal space. Feasible solutions are produced by mapping the random keys to points in the problem space. The QAP can be represented by generating a random uniform (0,1) variate for each facility to be assigned. To convert the random key representation to a literal solution, the index of the smallest random variable becomes the location assigned to the first facility, the index of the second smallest random variable becomes the location assigned to the second facility, etc. This sorting process continues until the index of the largest random variable is the location assigned to the nth facility. For a five-facility problem, the chromosome (.78, .23, .58, .94, .12) represents (5, 2, 3, 1, 4). This sequence is interpreted as facility 1 assigned location 5, facility 2 to location 2, etc.

Given two parents and site 3 randomly selected as the crossover site:

PA : .78 .23 .58 .94 .12 _ 5 2 3 1 4

PB : .46 .10 .07 .97 .51 _ 3 2 1 5 4.

Crossover is performed and the following offspring are produced:

OA : .78 .23 .58 .97 .51 _ 2 5 3 1 4

OB : .46 .10 .07 .94 .12 _ 3 2 5 1 4.

Neither offspring is infeasible, because the crossover operation is performed on the encoded solution and not the actual chromosome.

4.4 Implementation of the Genetic Algorithm

The solution procedure for the quadratic assignment formulation of Eq. (3.12), which assigns processes to locations within the foundry, is based on Bean s random keys approach. P.A. Djang and P.R. Finch developed Operator Tournament [15], a random keys software implementation which was used to construct the optimization model. Empirical results on test QAP cases using Operator Tournament indicate that the results produced by the software compare favorably to other evolutionary techniques such as simulated annealing, tabu search, or pure genetic algorithms. Population initialization and parent selection, genetic operators, and culling mechanisms are described in the following sections as they are implemented in the software.

4.4.1 Parent Selection

The creation of an initial population of solutions is the first step in the parent selection process. The population is initialized by generating chromosomes consisting of randomly assigned genes. Often a heuristic is applied in this step to produce an intitial set of good feasible solutions. Presumably, faster convergence to a final solution will be facilitated by an intelligent intialization process. Initialization of the population in this implementation was achieved by randomly generating a specified number of chromosomes. A heuristic added to initialize the population with a proposed layout produced negligible results, and was later deleted.

The purpose of parent selection from a population is to increase the overall probability that the most fit parents reproduce. Fitness is based on a measure of goodness determined by the value of the objective function. Parent selection based on fitness increases the chance that chromosomes with better values will contribute offspring to the next generation. One commonly used technique employs a biased roulette wheel parent selection. Davis [12] outlines the algorithm for roulette wheel selection in Table 4.1. The analogy to a roulette wheel comes from the assignment of proportionally sized slots to members of the population. Although roulette wheel parent selection is random, each parent s chance of being selected is proportional to its fitness.

4.4.2 Genetic Operators

Seven genetic operators are applied in the GA (in the order they are used): (1) Bernoulli crossover, (2) Bernoulli mutation, (3) simple mutation, (4) two-point crossover, (5) limited inversion, (6) inversion, and (7) four-point crossover. The following sections demonstrate the application of the seven operators using two parent solutions that represent the assignment of eight operations to eight locations,

Table 4.1 Roulette wheel parent selection

1. Sum the fitnesses of the population members; the result is the total fitness.
2. Generate a random number r between 0 and the total fitness.
3. Select the first population member whose fitness summed with the fitnesses of the preceding members, is greater or equal to r.

for example operation 1 is assigned to location 7, operation 2 is assigned to location 5, and so on. All operators are applied to the random keys encoded solutions and not the literal solutions. Again, the index of the smallest random variable (key) corresponds to the location assignment for facility 1. The sorting of keys continues until the index of the largest key becomes the location assignment for facility 8. The two parent solutions and their random key representations are shown in Table 4.2.

Table 4.2 Encoding Schemes for Two Parents

Parent	Literal encoding								Random keys encoding							
A	6	8	5	3	2	7	1	4	.86	.53	.27	.94	.21	.11	.62	.18
B	7	1	8	4	3	6	5	2	.20	.92	.59	.56	.88	.69	.16	.31

4.4.2.1 Recombination Operators

Crossover is the process where two parents exchange genetic material to produce an offspring chromosome. This is an extremely important operator in GA applications [12]. Many researchers claim that crossover differentiates GAs from other optimization procedures and evolutionary techniques that exclusively employ mutation. Crossover allows rapid recombination of desirable features in a manner that mutation cannot. The operator can produce offspring that are radically different from their parents; it acts to combine building blocks of good solutions from a diverse population.

Uniform or Bernoulli crossover is an operator that produces offspring by randomly determining which parent will contribute each gene of the child. If pc= the probability of a crossover, a random uniform (0,1) variate rg is generated and compared to the value of pc. If rg ≤ pc, then Parent A contributes the gene to offspring A; otherwise, Parent B contributes the gene. Offspring B is composed of the unused bits. An example is given in Table 4.3. with pc = .54. Offspring A is decoded to the solution (6 7 8 3 1 5 2 4). Offspring B is decoded as (1 5 8 2 4 3 7 6).

Table 4.3 Bernoulli crossover with p_c = .54

random variate r_g	.43	.81	.06	.53	.69	.12	.57	.29
Parent A	.86	.53	.27	.94	.21	.11	.62	.18
Parent B	.20	.92	.59	.56	.88	.69	.16	.31
Offspring A	.86	.92	.27	.94	.88	.11	.16	.18
Offspring B	.20	.53	.59	.56	.21	.69	.62	.31

In *two-point crossover*, two points on the parent chromosomes are randomly selected as crossover sites. The parents exchange genes between crossover sites to produce two offspring. If crossover sites 2 and 6 are randomly chosen (as indicated by the heavy lines), the crossover produces the offspring shown in Table 4.4.

Table 4.4 Two-point crossover with crossover sites 2 and 6

Parent A	.86	.53	.27	.94	.21	.11	.62	.18
Parent B	.20	.92	.59	.56	.88	.69	.16	.31
Offspring A	.86	.53	.59	.56	.88	.69	.62	.18
Offspring B	.20	.92	.27	.94	.21	.11	.16	.31

In this example of two-point crossover, Offspring A decodes to the solution (8 2 4 3 7 6 1 5). Offspring B decodes to (6 7 1 5 3 8 2 4).

Four-point crossover is very similar to two-point crossover, except that four crossover sites are randomly chosen. Suppose crossover sites 1, 3, 5, and 7 are randomly selected. The crossover operation results in the offspring shown in Table 4.5 (the crossover sites are indicated by the heavy lines).

Offspring A represents the solution (7 8 5 3 6 1 2 4). Offspring B is (6 1 3 8 4 2 7 5).

4.4.2.2 Reordering Operators

The inversion operator is used in GAs to obtain better ordering of genes, while crossover operators recombine genes to produce better schemata. Inversion can

Table 4.5 Four-point crossover with crossover sites 1, 3, 5, and7

Parent A	.86	.53	.27	.94	.21	.11	.62	.18
Parent B	.20	.92	.59	.56	.88	.69	.16	.31
Offspring A	.86	.92	.59	.94	.21	.69	.16	.18
Offspring B	.20	.53	.27	.56	.88	.11	.62	.31

reduce the defining length, δ(H), of valuable schema. Inversion is similar to 2-point crossover in that two points along the chromosome are randomly chosen to split the chromosome into three sections. Inversion will reverse the order of the genes in the cut section. Parents do not exchange genetic material in simple inversion. Table 4.6 illustrates the inversion operation on Parent A with points 3 and 7 indicated by the heavy lines. In this example offspring A decodes to a layout solution of
(5 8 6 3 2 4 1 7).

Table 4.6 Inversion with inversion sites 3 and 7

Parent A	.86	.53	.27	.94	.21	.11	.62	.18
Offspring A	.86	.53	.27	.62	.11	.21	.94	.18

Limited inversion is an additional reordering operator used in Operator Tournament. Two points are randomly selected to split the chromosome into three parts as in simple inversion. However, the inverted part is limited to one-third of the total genes to reduce the amount of churn that occurs.

4.4.2.3 Mutation Operators

Reproduction and crossover efficiently perform chromosomal recombination to produce new fit population members. Sometimes important schemata are lost in the process. The function of mutation in artificial genetic systems is to protect against these losses [18]. In GAs, mutation is the random alteration of a gene. Mutation rates are small in nature and similarly small in artificial systems, leading one to conclude that mutation operators are secondary to crossover operators in genetic schemes. Mutation procedures vary with problem-specific solution encoding schemes.

Table 4.7 demonstrates how a Bernoulli mutation is performed in this implementation on a random keys chromosome. Given a chromosome of length n, the probability of mutation p_m, and random uniform (0,1) variates r_g, where g = 1 to n, the gene is replaced by the value of the random variate if $r_g \leq p_m$.

Table 4.7 Bernoulli mutation for p_m = .008

random variate r_g	.801	.075	.060	.001	.575	.291	.333	.485
Parent A	.86	.53	.27	.94	.21	.11	.62	.18
Offspring A	.86	.53	.27	.001	.21	.11	.62	.18

The random keys representation of Parent A decodes to the solution (6 8 5 3 2 7 1 4). The mutation of one gene on the chromosome results in new solution (4 6 8 5 3 2 7 1).

In *simple mutation*, one gene is randomly selected from a chromosome and replaced with a random (0,1) value r. The operation is shown in Table 4.8, assuming a mutation of (randomly selected) gene 5 and r = .01.

Table 4.8 Simple mutation of gene 5 with r = .01

Parent A	.86	.53	.27	.94	.21	.11	.62	.18
Offspring A	.86	.53	.27	.94	.01	.11	.62	.18

In this case, the mutation of one gene on the chromosome results in new solution (5 6 8 3 2 7 1 4).

4.4.2.4 Population Improvement

Elitism is a culling mechanism that preserves the best chromosomes from one generation to the next; the fittest members of a population are copied to the next generation. The pitfall of this method is premature convergence to a non-optimal solution. However, introducing increased mutation rates maintains diversity for continued improvement and reduces the chances of premature convergence.

Djang and Finch s Operator Tournament favors successful operators. Each genetic operator is given at least one chance to contribute an offspring to the next generation. If an operator performs well, it is given additonal chances to insert offspring into the succeeding generation. Some operators may dominate production

of offspring in the first generations, but as the population converges to a solution, this effect is reduced.

Each member of a population is ranked by its fitness, or objective function value (Eq. (3.12)). Often the best members of a population, or those with the best fitness evaluations, fail to produce children in the succeeding generation. The implementation eliminates this loss by employing parental hypersampling which pools offspring chromosomes after all the operators have produced their allocation of chromosomes. The parent population is compared to the population of children and the best chromosomes from the two populations are retained [15]. In this manner, especially fit parents may survive several generations and may continue to generate better offspring.

Chapter 5

PRODUCTION CAPABILITY - A SIMULATION MODEL

5.1 The Casting Process

A detailed analysis of the complex interactions of material, personnel, material handling, and equipment in the casting operation cannot be represented in the formulation of a facility layout problem alone. Without additional evaluation of the interrelationships between a proposed layout under certain operating conditions such as production commitments, time constraints, personnel and equipment availability, and ionizing radiation, it is impossible to determine the production capability of the system. Simulation is a means of evaluating alternative layouts within the framework of an operating process.

The casting operation consists of 11 processes located in sixteen gloveboxes as shown in Table 5.1. There are a total of 17 gloveboxes in the foundry, including one unused box that is not dedicated to a process. An overhead trolley system connects the two glovebox lines and the storage vault, and is used to convey material bi-directionally. The trolley system is connected to the glovebox lines through two dropboxes. Dropboxes are used exclusively for passing material from one material transport device to another; no nuclear material processing or storage occurs in either dropbox. Each of the four trunklines contains its own material transport device that is capable of delivering material to each of the gloveboxes as well as the three interim

Table 5.1 Processes within the casting operation

PROCESSES	EQUIPMENT	# BOXES
Material Preparation	Hydraulic Press	1
Feed Casting	Feed Casting Furnace	2
Part Casting	Part Casting Furnace	3
Packaging	Work Box	2
Heat Treat A	Heat Treat Furnace	2
Heat Treat B	Heat Treat Furnace	1
Heat Treat C	Heat Treat Furnace	1
Oxide Roast	Oxide Roast Furnace	2
Density	Pycnometer	1
Non-destructive Assay	Neutron Assay Instrument	1

storage wells located on each trunkline. All material is contained within the glovebox line and is never handled externally to the gloveboxes or trunklines.

Two primary concurrent material flows occur in the casting operation - feed casting and part casting. Auxiliary activities include interim and long-term storage of in-process and completed parts, roasting of casting residues to oxides, non-destructive assay of oxides, packaging of oxides, and preparation of samples for analytical chemistry. The flowsheet for the casting operation is shown in Figure 5.1.

5.2 Model Design Considerations

An important aspect of designing a model is determining the features of the real-world system that need to be incorporated in the simulation. It is costly, and often unnecessary, to include every aspect of the system under investigation. Law

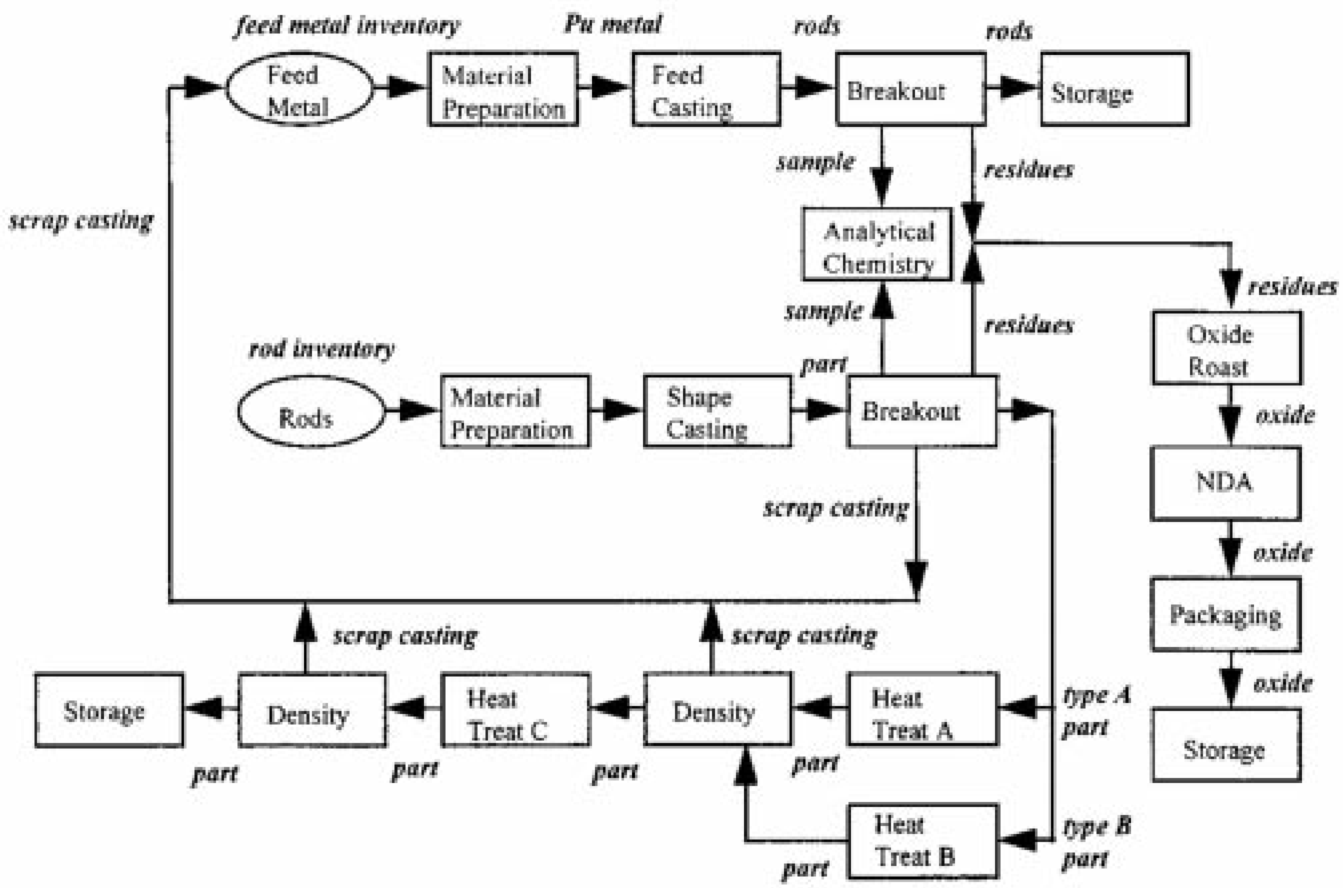

Figure 5.1 Flowsheet for the casting operation

and Kelton [28] recommend some general guidelines for establishing the level of detail required:

1. Define the issues of interest with the model users. Specify the performance indicators that must be provided to allow the users to make decisions. Determine how the model will be used and how often. A model is constructed for a specific purpose and cannot accurately estimate measures of performance for which it was not designed.
2. Consult experts of the system to determine the level of model detail. Concentrate on the most important aspects of the system. Model only to the level of detail that is consistent with the data available.
3. Start with a simple model and enhance it as required. Often, a simplified model of a system can aid in the determination of what features are important. This process reduces the chances of a major rewrite.

The intent of modeling the foundry at TA-55 is to determine (1) if the capacity of the existing process area is sufficient to satisfy the requirements of the Stockpile Stewardship and Management Program, and (2) that the baseline radiation exposure at a given production capacity is within DOE guidelines. Additional issues to be addressed are the utilization of the personnel assigned to the area, the utilization of the trolley system and the trunkline material handling devices, the necessity for in-line interim storage areas, and the utilization of key equipment. These model objectives were determined after many discussions with users and process experts. The model traces the movement of each entity through each location or process in the foundry. This approach is necessary to calculate personnel exposures from handling and storage of material and to ensure that criticality limits are not violated during the simulated operations. The simulation model tracks the progress of the casting processes every minute, since the process times for some operations and material transport times are on the order of minutes, not hours.

The casting operation is considered to be a terminating, non-steady-state system. A full shut-down of all processes occurs every six months when an inventory of all nuclear material is conducted. The inventory process lasts for one month after which operations commence from an empty-and-idle state. For this reason, there is no initial transient or warmup period associated with the simulation of the foundry.

5.3 Simulation Model Structure

The simulation was developed using the PC-based version of SIMAN V , a simulation language by Systems Modeling Corporation. The model is constructed to accept a solution from the output of the optimization model similar to the following:

Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Location	8	16	15	11	10	17	1	14	6	5	13	4	12	9	2	3	7

Here, process 1 or Material Preparation (from Table 5.1) is assigned to location 8, process 2 or Feed Casting 1 to location 16, etc. Solutions are presented to the model at run-time, and an input file is created that is specific for that solution. Each of the top 10 solutions from the optimization model was executed to obtain the output statistics necessary for the analysis of the competing layouts. The simulation model is divided into four functional components: (1) casting processes, (2) transportation of material, (3) interim storage of in-process materials and retrieval from storage locations, and (4) personnel exposure calculations.

5.3.1 Casting Processes

Two of the 11 processes in the casting operation, Material Preparation and Packaging, are completely manual and, although, processing can occur on overtime if necessary, all processing is assumed to occur on a single shift. The remainder of the processes can proceed unattended overnight and on the weekends when the facility is closed once a technician completes the initial attended portion of the process. The technicians assigned to the foundry are cross-trained to operate any glovebox equipment and are not assigned to a specific process. When a technician is not being utilized in the foundry, he is assigned to duties away from the processing area; however these job functions are not included in the simulation model. Each of the 16 gloveboxes is represented in SIMAN V as a STATION where a variety of processing steps can occur. Figure 5.2 shows a simplified version of the representation of a casting process station.

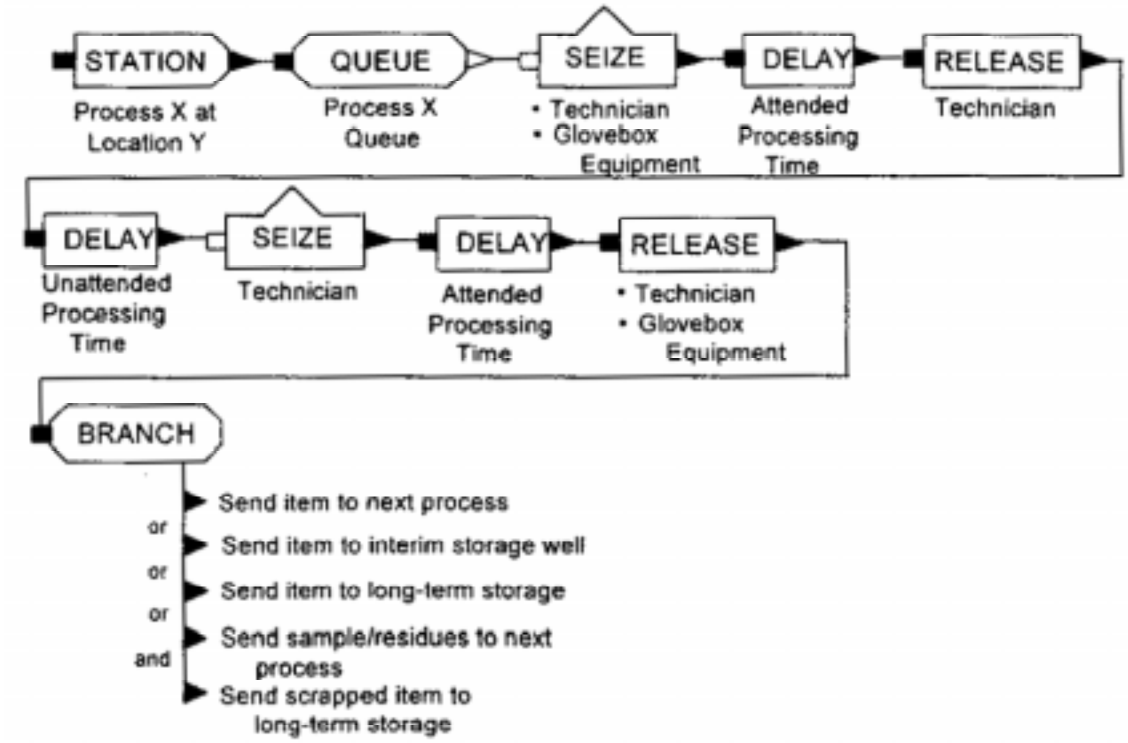

Figure 5.2 Representation of a casting process station

Each process is represented by a station that is assigned to a particular location in the foundry. Material enters the station and waits in a queue until a technician is available, after which a delay is introduced to represent the attended processing time. The technician is then released while the process proceeds unattended. Again, the technician is seized and performs the task of unloading the material before it is sent to the next process. The material can follow several paths depending on whether it is scrapped, fails and needs rework, is divided into separate components, or needs further processing.

5.3.2 Transportation of Material

Five material transport devices are located in the foundry, the semi-automatic trolley system and four manual trunkline systems. Each device can only transport one container of material at a time due to criticality concerns. Thirty-two transporter delivery points consisting of 17 glovebox locations, 2 dropboxes, 12 storage wells, and a storage vault. Connecting these delivery points are 118 bi-directional paths that material can follow. Before material can be moved from one location to the next, a series of system status conditions must be true:

1. Is a radiation worker available?
2. Is every transporter device that will be required available?
3. Is the receiving location empty?
4. Does the pass-thru dropbox (Figure 1.1) have capacity for the item?
5. Is the receiving location equipment unallocated?

An item can be scheduled to move to a new location only if each condition is true. This process results in long transportation delays between seemingly short distances. Figure 5.3 illustrates how (in general) the transportation of material from station to station is implemented in SIMAN V .

Once a process is completed, material is sent to a transporter queue where the conditions for transportation are checked (SCAN block). If all conditions are true, the entity seizes a technician and allocates the destination glovebox equipment. An entity may require as many as three transporters to reach its final destination; each

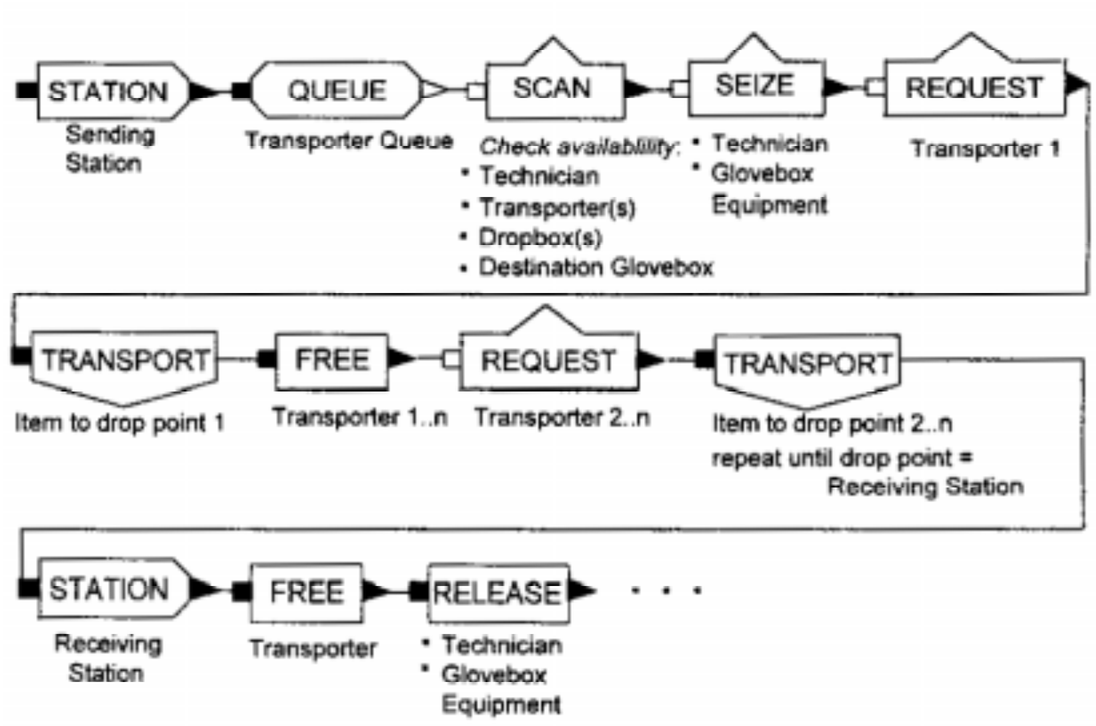

Figure 5.3 Representation of material transportation

transporter is requested individually and the material is incrementally moved to drop points until the item arrives at the receiving station.

5.3.3 Interim Storage

Each trunkline contains three wells that are used as interim storage for in-process material from the density glovebox and the three heat treat furnaces. The three wells adjacent to the material preparation glovebox are dedicated to that process, and cannot be used as storage for other in-process material. This processing strategy accommodates criticality limits in the material preparation glovebox, but often results in long transportation times for material that must travel from a glovebox in one trunkline to a well location in another. The structure in the simulation model for retrieving items from a well location or for storing material in one is illustrated in Figure 5.4.

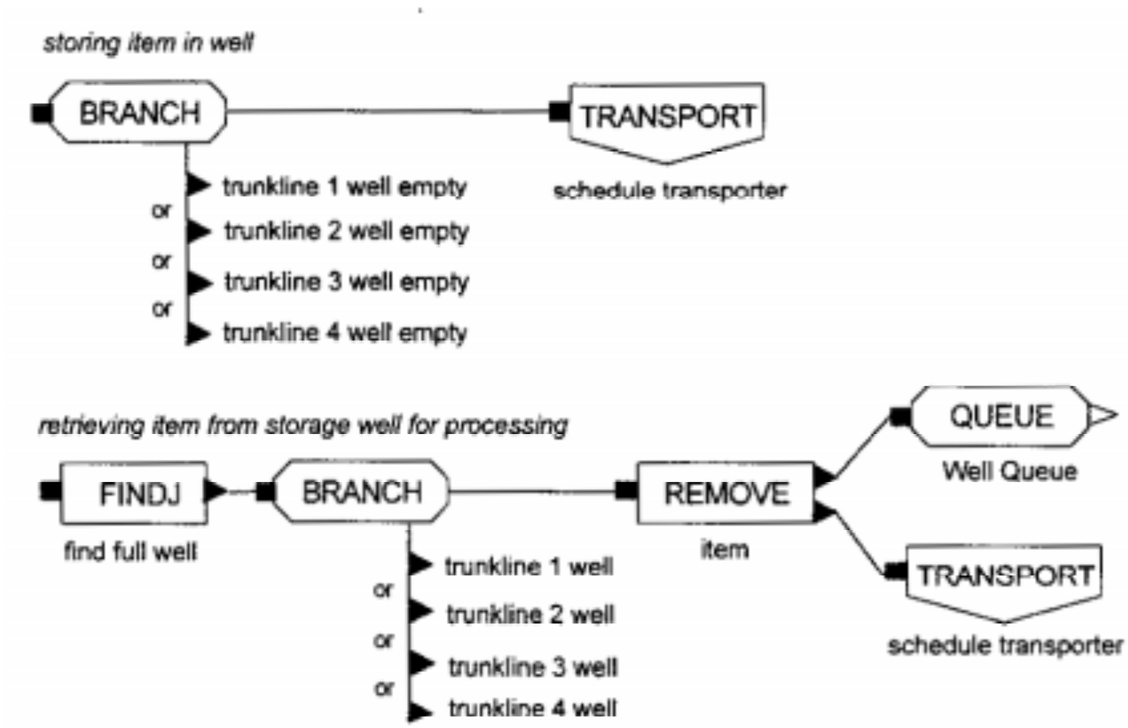

Figure 5.4 Representation of interim storage

Material is sent to interim storage from material preparation and heat treat. The simulation locates the closest empty well and schedules the material for transport. Items are retrieved for processing from the well locations by material preparation and density. The model finds a well that contains the material it needs, and removes the item from the particular well queue. It then schedules the material for transport to the station.

5.3.4 Personnel Radiation Exposures

There are two components of the dosage calculations, direct exposure from material in the immediate working area and background radiation from material residing in adjacent processing and storage locations. All dose calculations are based on a weighted average of gamma and neutron doses for a particular matrix of nuclear material (metal, cast parts, oxides, residues, etc.). Dose rates are taken from measurements of gamma and neutron radiation made at the existing gloveboxes in the foundry. All measurements were conducted at an operating distance of 30 centimeters from each glovebox. Differences in the dose rates can be attributed to the shielding on the individual gloveboxes and storage well locations and the amount (and matrix) of nuclear material present in the various locations. Background radiation exposure from nuclear material situated in adjacent locations varies as the inverse square of the distance from the source. For example, given a dose rate measurement of 5 mRem/hr taken at a glovebox and a distance of 10 feet between gloveboxes, the dose rate is 5 /102 or .05 mRem/hr. The dose rates for the individual glovebox processes used in the technician exposure calculations are listed in Table 5.2.

The exposure calculation in the simulation model takes a different form than that of the optimization model objective function of Eq. (3.12). Each entity that

Table 5.2 Measured dose rates at various locations in the foundry

Location	Dose rate (mRem/hr)
Material Preparation	7
Feed Casting	5
Part Casting	3
Packaging	2
Heat Treat A	3
Heat Treat B	3
Heat Treat C	3
Oxide Roast	5
Density	4
Non-destructive Assay	5
Well Storage	5

flows through a process in the simulation model contributes an amount of radiation dose as expressed in Eq. (5.1)

$$\sum_{i=1}^{nentities}\sum_{j=1}^{nprocs} AT(i,j)SNM(i,j)DR(i,j) + \left. \sum_{k\in S(a_j)} \frac{AT(i,j)SNM(e_k,p_k)DR(e_k,p_k)}{dist^2(a_j,k)} \right) \tag{5.1}$$

where,

nentities = number of entities generated during a simulation run,

nprocs = number of processes performed per entity,

a_j = location assigned to process j,

e_k = entity in location k,
p_k = process to which location k is assigned,
$S(a_j)$ = set of locations within 15 feet of process j where $j \neq k$,
AT = worker attended service time (minutes),
SNM = amount of nuclear material (grams),
DR = radiation dose rate (mRem/gram-hr), and
$dist^2$ = distance (squared) between locations (ft^2).

The first term in the equation obtains the direct exposure from each process (i=k in Eq. (3.12)). The second term, summed over locations k, adds the background radiation exposure from material located in adjacent gloveboxes and storage locations (i k in Eq. (3.12)).

5.4 Input and Output Data for a Stochastic Process

5.4.1 Simulation Input

Stochastic systems possess input parameters and, subsequently outputs, that exhibit random behavior. Often the most difficult decision a modeler faces is determining the appropriate method to represent input data. The decision to represent each data input as deterministic or probabilistic largely depends on availability and relevance to the purpose of the model.

Input data for the casting operation was obtained from three sources: (1) processing information at the Rocky Flats Plant, (2) subject matter experts at Los Alamos, and (3) desired operating parameters defined by the DOE. Inputs to the simulation model and their representations are shown in Table 5.3.

Table 5.3 Data inputs for simulation modelInput Parameter

Input Parameter	Representation
Number of technicians	Deterministic
Number of gloveboxes	Deterministic
Rework	Probabilistic
Process times	Probabilistic
Transportation times	Probabilistic
Shift schedules	Deterministic
Nuclear material quantities	Probabilistic
Radiation dose calculations	Deterministic
Failures	Probabilistic
Routing	Deterministic
Simulation run length	Deterministic

5.4.2 Simulation Output

A simulation model mimics the complex dynamic behavior of a system over time in order to estimate the true characteristics of the system. Recording time-persistent and observational variables is the mechanism for obtaining output data that is used in the estimation of population parameters from sample data. Time-persistent variables are those for which values are defined over time. For example, determining the utilization of technicians requires both the knowledge of the random variable busy technicians, which may take on different values over time and the time periods for which each value persisted. Statistics based on observational variables are concerned only with the value of each observation, and not the time it occurred. An example of an observational variable is the time an item waits for a material transporter.

The capacity of the foundry is determined based on the assumption that two types of weapon components will be fabricated during each 6-month time period. For the purposes of this dissertation, these types will be identified as Type A and Type B. The summation of Type A and Type B castings produced indicates the capacity of the system given the input parameters listed in Table 5.3.

SIMAN V provides the user with the ability to obtain output statistics for any performance measure of interest. The drawback to this capability is that the analyst is faced with a daunting amount of data, and must decide between what is pertinent and what is superfluous. The foundry model generated statistics on everything from queue sizes for the trolley system to the utilization of the trunkline transporters. In a practical sense, many of the utilization statistics produced were used for determining processing bottlenecks. Successive generations of the model incorporated this information to produce a simulation that more accurately reflects the casting
operation. The output statistics that were used to distinguish differences in processing strategies are shown in Table 5.4.

5.5 Statistical Analysis for a Terminating System

Consider a ordered set of events $X_1, X_2, ..., X_n$ where n is a positive integer. If the outcome of each event is governed by random behavior, the series $X_1, X_2, ..., X_n$ is termed a stochastic process [16]. The single sequence of numbers assumed by a

Table 5.4 Measures of performance for the casting operation

Measure of Effectiveness	Use	Type
Casting capacity	Primary MOE	Observational
Background exposure	Primary MOE	Observational
Total exposure	Secondary MOE	Observational
Total transportation time	Secondary MOE	Observational
Technician utilization	Secondary MOE	Time-persistent
Equipment utilization	Secondary MOE	Time-persistent
Transporter utilization	Secondary MOE	Time-persistent
Time in system for feed casting	Secondary MOE	Observational
Time in system for Type A casting	Secondary MOE	Observational
Time in system for Type B casting	Secondary MOE	Observational

stochastic process is called a realization; if $n \to \infty$, then X_n assumes an infinite number of values, resulting in an infinite number of realizations. Due to time and cost contraints, an analyst cannot observe every event, but observing a subset of events is feasible. This subset, called a *time series*, is a finite realization of a stochastic process. Statistical inferences about the underlying distribution concerning one event improve as the sample size increases. Similarly, statistical inferences improve for n events as the number of observed time series or *replications* increase. One replication represents one individual run of a simulation experiment.

5.5.1 Point Estimates and Confidence Intervals

Performance measures for a simulation are dependent on the conditions under which each replication of a simulation is executed [28]. Independence is achieved by using different random numbers for each replication, a common feature in most simulation languages. Another important consideration is the state of the system at the beginning of each replication. Every replication must start from same the set of initial conditions to ensure that output variables will be comparable. If X_i is a random variable defined on the ith replication of n replications, and the X_i's are comparable between replications, then the X_i's are considered independent, identically distributed (IID) random variables.

Given a set of IID random variables, one can obtain a point estimate and confidence interval for the mean $\mu = E(X)$. The sample mean

$$\overline{X}(n) = \frac{\sum_{i=1}^{n} X_i}{n} \tag{5.2}$$

is an unbiased point estimate of μ, given a large number of independent replications of the simulation experiments has been performed, each generating an X(n). The sample variance

$$S^2(n) = \frac{\sum_{i=1}^{n} \left[X_i - \overline{X}(n)\right]^2}{n-1} \tag{5.3}$$

is similarly an unbiased estimator of _ 2. Given a sample mean X(n) and a sample variance S 2(n) computed from a sample of a normal population, a 100(1 - _)% confidence interval for μ is given by

$$\left[\overline{X}(n) - t_{\alpha/2,n-1}\sqrt{\frac{S^2(n)}{n}},\quad \overline{X}(n) + t_{\alpha/2,n-1}\sqrt{\frac{S^2(n)}{n}}\right] \tag{5.4}$$

The 100(1 - α)% applies only to a confidence interval computed for a single measure of performance. More often, an experimenter is interested in simultaneously constructing confidence intervals for multiple MOEs [28]. If there are k MOEs of interest, the probability that all k of the confidence intervals will contain their true means is expressed by the Bonferroni inequality:

$$P(\mu_s \in I_s \text{ for all } s = 1,2,\ldots k) \geq 1 - \sum_{i=1}^{k} \alpha_i \tag{5.5}$$

The importance of the Bonferroni inequality in analyzing simulation output is the degree of confidence one can place on the confidence intervals constructed for each MOE. If there are three MOEs of interest, each constructed using _=.05 or a 95% confidence interval, one can only conclude the probability is at least 1 - $\sum\alpha_i$ (for i=1 to 3) or 85% that all three confidence intervals simultaneously contain the true means. If there are 10 MOEs, the probability decreases to (at least) 50%. This illustrates the importance of determining which performance measures produce the most significant information in the analysis of a simulation model.

5.5.2 Analysis of Variance

Analysis of variance (ANOVA) refers to statistical procedures used for analyzing experimental results when more than two treatments have been performed [14]. The characteristic that is being studied for each treatment is referred to as the response. In the foundry simulation, one response is total castings produced. The treatments of the experiment are the 10 layout configurations. The purpose for performing an analysis of variance is to determine whether the differences in the true average for each treatment or level are statistically significant. The null hypothesis H0 states that there are no differences in the population means; the alternative hypothesis Ha is that at least two of the means differ. Given k treatments, the problem can be stated as:

H0: $\mu 1 = \mu 2 = \mu 3 = \bullet\bullet\bullet = \mu_k$ versus H_a : at least two μ_i's differ.

X_{ij} represents a random variable from the jth replication of the ith treatment, and all X_{ij} s are assumed independent. Restricted to the case where the sample sizes for each treatment are equal, let J = the total number of replications for each configuration and I = the total number of configurations. The data set contains a total of IJ observations. The mean of the replications for the ith treatment or configuration is

$$\overline{X}_{i\cdot} = \frac{\sum_{j=1}^{J} X_{ij}}{J} \tag{5.7}$$

The average of all observations is called the grand mean and is defined as

$$\overline{X}_{\cdot\cdot} = \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} X_{ij}}{IJ} \tag{5.8}$$

Two assumptions underlie the use of single-factor ANOVA: (1) the treatment distributions are normal, and (2) the variances of the treatment distributions are equal. If H_0 is true, each of the X_{ij}'s should come from the same population distribution with mean μ and variance σ^2. The means for the samples, the $X_{i\bullet}$'s, should be close to one another and the grand mean, $X_{..}$. The statistic mean square for treatments or MSTr is an estimate of σ^2 based on the differences between the sample means. It is given by

$$MSTr = J\left\{\frac{\sum\left(\overline{X}_{i\cdot} - \overline{X}_{\cdot\cdot}\right)^2}{I-1}\right\} \tag{5.9}$$

When MSTr = 0, the $X_{i\bullet}$'s are equal. As the difference between the $X_{i\bullet}$'s becomes larger, the value of MSTr becomes larger. The statistic is an unbiased estimator of σ^2 when H_0 is true, but can overstate σ^2 when H_0 is false. The mean square for error or MSE statistic is an unbiased estimator of σ^2 whether H_0 is true or false. Each sample is assumed to come from a population having the variance σ^2 ; this variance can be estimated by any of the sample variances. The MSE statistic is defined as

$$MSE = \frac{S_1^2 + S_2^2 + \cdots + S_I^2}{I} \tag{5.10}$$

The ratio MSTr/MSE is the value of a random variable having a F distribution with I-1 and I (J-1) degrees of freedom. The null hypothesis will be rejected if the computed value of F exceeds the tabular value of F _,I-1,I (J-1) with significance level _. If the null hypothesis is rejected, supplementary methods can be used to determine which treatments are significantly different [14].

5.5.3 Selecting the Best Systems

The ANOVA of Section 5.5.2 is sensitive to its equal variance assumption. If the equal variance condition fails, another method is available providing the Xij s are normally distributed. Law and Kelton [28] takes the analysis of alternative systems one step further by ranking treatments according to a performance measure and selecting the m best out of k alternatives.

The Law and Kelton method assumes independence of treatments and normality of the X_{ij}'s, but most importantly, the variances, σ_i^2's, do not have to be known or equal. This approach has three objectives.

1. The probability of selecting a subset m of k treatments that contains the smallest mean response will be greater than or equal to the probability specified by the analyst, *P**, which must be greater than *m!(k-m)!/k!*
2. If two means are very close (and in a practical sense, not significantly different), the method must be robust enough to avoid making a large number of unnecessary replications to account for the difference between the means.
3. The selected subset will contain, with probability *P**, a system with an expected response no greater than the expected response of the worst of the m selected solutions + *d**, where *d** is a user-assigned indifference amount.

The method is a three-step procedure. First, the procedure is initialized by taking a sample of n0 initial replications and calculating the sample means, $X_i(n_0)$, and variances,

$S_i^2(n_0)$, for each of the k configurations. The variance estimates are used to determine the total number of replications Ni needed to make a selection of the best m of k systems in the second step.

$$N_i = \max\left\{n_0 + 1, \left\lceil \frac{h^2 S_i^2(n_0)}{(d^*)^2} \right\rceil\right\} \quad \text{for } i = 1, 2, \ldots, k \tag{5.11}$$

Here, h is a tabular value based on the values of n0, P*, and k (the values of h can be found in Appendices 10A and 10B in Law and Kelton [28]).

In the second step, Ni - n0 additional replications for each system are performed and the k system means are calculated for the extra replications. The final step involves calculating the weighted means over all the replications, Ni. The weighted means serve as the basis for system selection. The weights are calculated as follows:

$$W_{i1} = \frac{n_0}{N_i}\left[1 + \sqrt{1 - \frac{N_i}{n_0}\left(1 - \frac{(N_i - n_0)(d^*)^2}{h^2 S_i^2(n_0)}\right)}\right] \tag{5.12}$$

$$W_{i2} = 1 - W_{i1}, \quad \text{for } i = 1, 2, \ldots, k. \tag{5.13}$$

The weighted sample means are defined as

$$\tilde{X}_i(N_i) = W_{i1}\bar{X}_i^{(1)}(n_0) + W_{i2}\bar{X}_i^{(2)}(N_i - n_0). \tag{5.14}$$

where,

$\overline{X}_i^{(1)}(n_0)$ is the mean of the ith system using n_0 replications, and
$\overline{X}_i^{(2)}(N_i - n_0)$ is the mean of the ith system using $N_i - n_0$ replications.

The selected subset is defined as the m systems with the smallest values of $X_i(N_i)$'s.

Chapter 6

RESULTS

6.1 The Optimization Model

Djang and Finch s GA implementation for the solution of the foundry QAP was executed on a PC with a Pentium™ processor. A population size of 17 was used for 20 generations. The GA converged to a solution after 16 generations after approximately five seconds of execution time. The implementation provides for dynamic assignment of genetic operator contribution rate based on the success of each operator during the evolutionary process. This feature eliminates the need to a priori selection of crossover and mutation rates [15].

The input parameters to the GA are (1) distance (in feet) between locations in the foundry, (2) radiation dose rate from each of the 16 processes, (3) attended service time for each process, and (4) the constant expected production capacity for the foundry. The fitness evaluation of Eq. (3.11) produces an exposure index for each configuration which is used to rank the top solutions from the optimization model. This index represents an upper bound on actual personnel exposures, because the value is calculated using a full material loading in each glovebox in the foundry. In addition to the exposure index calculation, a cost is computed for each layout configuration. Some gloveboxes in the current configuration of the foundry are prohibitively expensive to relocate due to size or contamination concerns. Other gloveboxes are scheduled for decomissioning and decontamination, and the cost to replace them is zero. The solution procedure considers these relocation costs and assigns a cost term for each solution. No attempt is made to minimize the costs; they are simply reported. The input parameters for the calculation of relocation costs are original location assignment of each foundry process and the cost to relocate (if any) each process.

The exposure indices and relocation costs associated with the top ten solutions produced by the optimization model are listed in Table 6.1. The assignment of locations to processes for the top ten solutions is illustrated in Table 6.2. For example, the solution 1 layout assigns material preparation to location 7, feed casting 1 to location 11, etc.

Table 6.1 Exposure indices and relocation costs for the top ten solutions

Solution	Exposure Index (Rem/worker)	Relocation Cost ($K)
1	2.076	455
2	2.077	400
3	2.077	415
4	2.077	430
5	2.078	430
6	2.078	430
7	2.078	430
8	2.078	415
9	2.078	355
10	2.079	415

Table 6.2 Assignment of locations to processes within the foundry

Process	Solution									
	1	2	3	4	5	6	7	8	9	10
Material Preparation	7	3	1	15	1	9	17	14	7	7
Feed Casting 1	11	2	3	7	3	6	12	11	9	11
Feed Casting 2	2	7	16	2	4	7	5	7	11	17
Shape Casting 1	6	4	7	11	5	10	10	2	6	8
Shape Casting 2	17	15	11	1	7	8	1	9	12	9
Shape Casting 3	4	11	15	16	16	2	7	17	8	2
Packaging 1	13	1	2	13	13	13	2	1	13	4
Packaging 2	14	14	14	14	14	14	14	15	1	14
Heat Treat A1	10	12	13	10	6	16	16	3	10	3
Heat Treat A2	5	17	4	3	15	4	13	13	16	15
Heat Treat B	3	10	9	6	17	3	9	8	2	10
Heat Treat C	12	8	12	4	12	5	15	5	15	5
Oxide Roast 1	16	9	17	5	10	11	4	4	17	1
Oxide Roast 2	1	5	10	17	2	1	8	6	5	12
Density	15	6	5	9	8	12	11	10	3	13
Non-destructive Assay	9	13	6	12	9	15	6	12	14	6
Unused glovebox	8	16	8	8	11	17	3	16	4	16

6.2 The Simulation Model

Each of the ten top layout solutions generated by the optimization model was presented to the simulation model. The simulation model is constructed to accept any configuration solution at run-time. This feature eliminates the need to develop an individual simulation for each configuration; however, solution-specific input files are generated for each configuration. Set-up time for running each solution is on the order of one hour; execution time for each replication of the simulation model is 11 seconds on a PC with a Pentium processor.

The number of replications to be run for each configuration was determined by iteration. Initially, 10 replications of the model were run. The confidence intervals were calculated and determined to be too large. Twenty replications provided an acceptable confidence interval.

The time frame for the simulated system is 6 months: 5_ months for production and _ month for inventory. The two primary measures of effectiveness are the number of castings produced and the background radiation exposure per radiation worker. The number of castings produced is indicative of the capacity of the foundry for a 6 month time period. Background radiation exposure is a component of total radiation exposure, and is a function of the assignment of gloveboxes to locations in the foundry. Radiation worker exposures increase if high-dose-rate gloveboxes are located adjacent to each other.

6.2.1 Primary Measures of Effectiveness

The two primary MOEs, castings produced and background exposure per radiation worker (expressed in mRem), require testing for statistically significant differences between the treatment means. The preferred method is ANOVA (described in Section 5.5.2) which requires that the treatments are normally distributed with equal variances. Prior to performing an ANOVA, tests were conducted to verify whether there was significant evidence to deny either of these properties. The simulation output data for the two primary MOEs for each of the 10 solutions (20 replications) are included in Appendix A.

Goodness-of-fit tests are used to evaluate if a set of empirical data statistically differs from a specified theoretical distribution. The Kolmogorov-Smirnov (K-S) test is one goodness-of-fit test that measures the deviation of an observed sample distribution from a theoretical distribution. The K-S test was performed on the 20 replication means for each of the 10 layout of the two MOEs, castings produced and background exposure, to determine if the sample distributions are normally distributed. For _=.05, all treatments for the 2 MOEs passed the normality tests with one exception. Treatment 7 failed the normality test for background exposure. Treatment (or solution) 8 failed the normality test for castings produced, at _=.10.

The equal variance property was investigated by using an F-test on the variance ratio of pairs of treatments for both MOEs. Two of the 45 pairs failed at _=.05 for castings produced, a reasonable result given that the expected failures under H0 is greater than two. Background exposures had 20 failures out of 45 pairs. The ANOVA test is not an appropriate choice as an analysis tool for this MOE given unequal variances between the treatments.

A single-factor analysis of variance was performed for the MOE, castings produced, to test H0 that all layout configurations have the same mean casting production. The ANOVA summary for castings produced is shown in Table 6.3.

Table 6.3 ANOVA for castings produced

Source of variation	*d.f.*	*Mean Square*	*F*	$F_{.05, 19, 190}$
Treatments (configurations)	9	$MSTr = 3.294$	$MSTr/MSE=$	1.88
Error	190	$MSE = 5.957$	.553	

Because the value of F calculated for castings produced, 0.553, did not exceed $F_{.05, 9, 190} = 1.88$, H_0 is not rejected at significance level .05. The differences in means for the number of castings produced for the 10 treatments do not differ significantly.

The analysis approach of Law and Kelton [28] described in Section 5.5.3 was used for the MOE, background exposure. This method assumes that the treatments are normally distributed; however, the procedure does not assume equal variances among the treatments. Law and Kelton s approach is dependent on a computed sample size which is sensitive to the total treatments considered. The initial 10 layout configurations were reduced to the best five, to reduce the number of additional replications to be performed for each treatment. Layouts 10, 5, 8, 9, and 1 were selected based on the lowest mean background exposures for 20 replications. Solution 7 was omitted from consideration, because it failed the K-S test for normality. A sufficient number of good layouts were available for analysis even with the omission.

Table 6.4 summarizes the computation of Ni and Xi(Ni) for each of the 5 configurations. The data for Ni replications of each solution are in Appendix B. For the analysis, $P^* = .95$, $h = 3.507$, and $d^* = 1$. The ranking of the top three of the five solutions did not change with additional replications. The analysis determined that the top three solutions are 10, 5, and 8.

6.2.2 Secondary Performance Measures

Although these data are not considered in determining the optimal layout,

Table 6.4 Determining Xi(Ni) for top 5 solutions

Solution	$\overline{X}_i^{(1)}(20)$	$S_i^2(20)$	N_i	$\overline{X}_i^{(2)}(N_i\text{-}20)$	$X_i(N_i)$
10	17.88	1.332	16	17.88	17.88
5	19.50	2.377	30	19.85	19.39
8	20.44	10.78	133	20.63	20.57
9	22.41	4.402	55	22.22	22.35
1	22.61	9.439	117	22.04	22.23

secondary performance measures are useful in developing an operating strategy for the foundry. Total exposure per radiation worker (expressed in Rem) is one of the most important statistics in analyzing the results of the simulation model. If the exposure per worker exceeds allowable limits, alternative strategies must be developed for processing. High total material transportation times indicate inefficiences in the individual layouts. The amount of time that a component spends in the foundry (from the time the feed material is delivered until the finished unit is stored) is useful in materials requirements planning and determining product mix. Planning for the efficient use of the resources requires knowledge of operating parameters such as utilization of personnel and equipment.

Table 6.5 summarizes the average values of the secondary performance measures for the three top solutions (layout configurations). The means were obtained using all replications performed (Ni) as a result of the analysis in
Section 6.2.1. The performance measures summarized are (1) average exposure per worker, (2) average material transport time, (3) average time in system for rods, type

Table 6.5 Summary of secondary performance measures

	Solution		
Statistic	**10**	**5**	**8**
Exposure/worker (Rem)	1.15	1.15	1.15
Material transport time (minutes)	2290	1954	1890
Time in system (minutes):			
rod castings	3406	3415	3423
type A castings	14720	14596	14652
type B castings	24923	24453	24990
Utilization (percent):			
radiation worker	75	74	75
material preparation	74	74	74
density	15	15	15

A castings, and type B castings, (4) utilization of radiation workers, and (5) utilization of two processes that were considered to be bottlenecks in the casting operation, material preparation (press) and density. The data for the secondary performance measures are included in Appendix C.

Radiation worker utilization was much higher than expected. For planning purposes, personnel are generally assumed to be 50% utilized on the operating floor. This allows time for related activities such as paperwork, training, meetings, vacation, and employee development. The density utilization was much lower than anticipated; however, all part castings are routed through density, and a pycnometer failure could cause extensive delays. The same is true of the press in material preparation.

6.2.3 Selection of a layout configuration

The analysis of the performance measures for the simulation produced many surprises. There were no discernable differences between the layout configurations for capacity, total personnel exposure, process/equipment utilization, or radiation worker utilization. A statistic that varied between solutions was transportation time. Although the utilization of the transporters was very low (less than 2%), the simulation model demonstrated that transporter grid-lock was a common occurrence. Therefore, the layout configuration that minimizes material movements is one that minimizes transporter grid-lock. Additionally, material flowing through the foundry is a small fraction of the material that utilizes the trolley system. Material also flows from machining and assembly to the storage vault via the trolley.

The determination of the best layout configuration must take into account expert knowledge of the system being studied in addition to the performance measures. Layout 5 was the most feasible layout from an operational standpoint. The primary casting furnaces are located in close proximity to the material preparation glovebox. The three highest radiation processes are located in the back of the room. Lastly, seldom used backup gloveboxes are located in high-traffic trunklines, which frees up more interim storage for highly utilized processes. The configuration of the foundry using solution 5 is illustrated in Figure 6.1.

A point estimate and confidence interval for the two MOEs (for solution 5) were calculated using the fixed-sample-size procedure given in Eqs. (5.2) - (5.4). The 95% confidence intervals were computed using n = 30 and _ = .05 as shown in

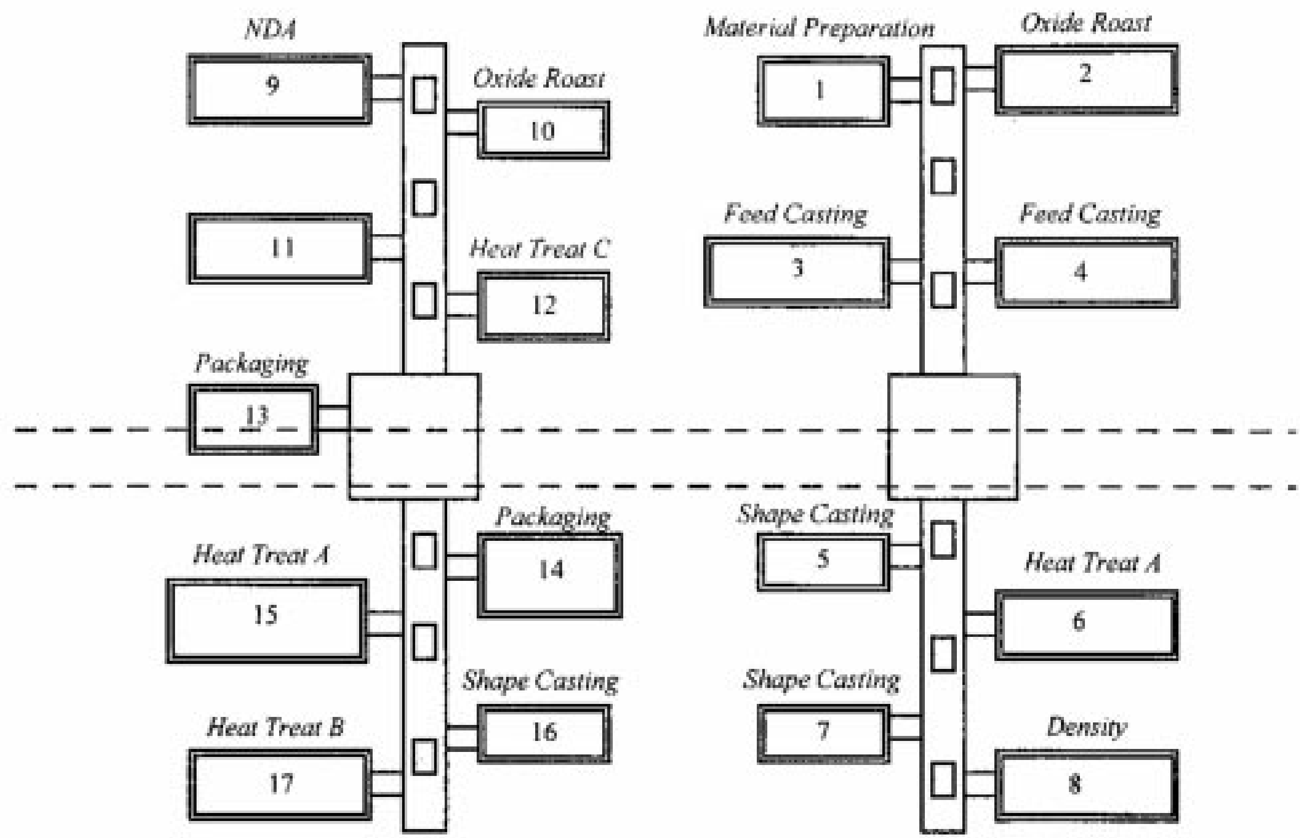

Figure 6.1 Configuration of the foundry using solution 5

Table 6.6. The means for the castings produced and background exposure were obtained from 30 replications of the simulation.

Table 6.6 Confidence intervals for primary MOEs for solution 5

Castings Produced	Background Exposure (mRem/worker)
54 ± 1	19.62 ± .63

The mean for the background exposure is not the same weighted mean calculated for the solution comparison procedure in Table 6.4. Note that simultaneous confidence intervals were constructed for the primary MOEs. The Bonferroni inequality (Eq. 5.5) states that if confidence intervals are constructed for two measures of performance, then the probability that each of the intervals contains its true measure is greater or equal to 100(1- 2α) or 90%.

An additional finding from the simulation model was the need for additional in-process storage. The first simulation models were constructed without in-line storage wells, and the results were similar to the transporter grid-lock experienced. One of the operating parameters for the model was the elimination of bagouts for in-process material. Bagouts are the process of removing nuclear material from a glovebox line resulting in additional processing time, waste generation, and exposure. In-line storage mitigates the need for bagouts by providing a location to place material (within criticality limits) until the next process is available. The current simulation model incorporates twelve storage wells; however, the simulation model proved more interim storage locations are needed to accomodate the quantities of nuclear material present in the system at a given time.

Chapter 7

CONCLUSIONS AND FUTURE DIRECTIONS

This chapter concludes this work with a discussion of the effectiveness of the methodologies developed to simulate the foundry, the major contributions of the research, and future directions for research. Section 7.1 provides an assessment of the results. Section 7.2 summarizes the contributions. The final section presents an area that warrants future study and evaluation.

7.1 Assessment of Results

The function of the integrative modeling approach was to first produce a set of good layout configurations subject to the constraints imposed by the problem formulation and then to assess the merits of each configuration. The GA produced 10 layouts with excellent features where exposures are minimized. Establishing a set of layout configurations by relying solely on the experience of process experts is not the best procedure to follow, because the operating parameters for the future casting operation do not reflect operating scenarios of the past. In Chapter 6, layout configuration number 5 was chosen to be a candidate for the proposed layout of the foundry based on the statistical tests performed. The final layout will be determined by examining the features of each of the top configurations and combining the best of the features.

The exposure index generated for each layout configuration by the optimization model represents the worst case exposure per radiation worker in the foundry. The index was did not reflect the value obtained in the simulation model for exposure per worker or the final ranking of solutions. This is due to the lack of variability in the computation of exposures by the fitness evaluation as opposed to the dose calculation of the simulation model. Figure 7.1 depicts a glovebox with adjacent boxes and well locations (designated by letters).

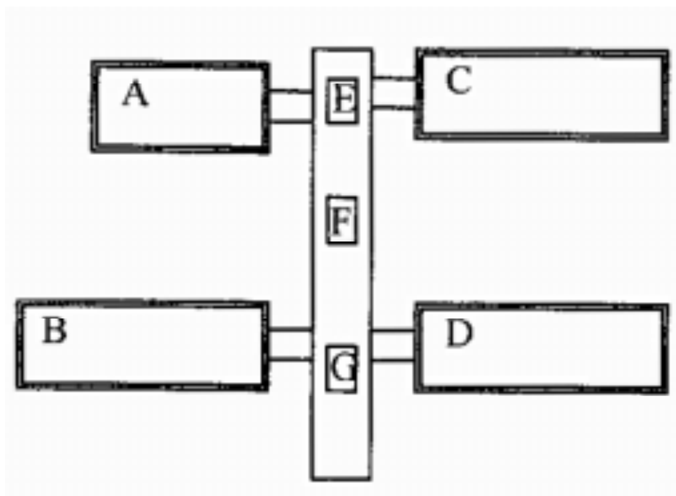

Figure 7.1 Section of trunkline showing adjacent locations

If the fitness evaluation computes the exposure to a technician operating at glovebox A, the dose would be calculated as though locations B, C, D, E, F, and G were each producing a maximum background exposure for the duration of the attended process at A. The simulation model calculates the exposures due to adjacent locations based on the nuclear material that is actually present in the other locations during the operation at glovebox A. Thus, if nuclear material is only present in well locations B, C, and D, there is no dose contribution from locations E, F, and G. A method for introducing variability into the optimization model to more closely represent what occurs in the simulation model is to define probabilities of material being present at a given location. The output from the simulation model provides insight into the appropriate values for the probabilities.

7.2 Research Contributions

In this dissertation we have investigated the effectiveness of a dual-model approach to simulating a casting operation at a nuclear facility. No attempt was made to evaluate if a GA methodology is the best solution search paradigm for the QAP; however, the GA produced a set of good, practical layout solutions in less than five seconds of execution time. The representation of the foundry involved developing two models: (1) an optimization model that produces a set of optimal layout configurations, and (2) a simulation model that determines the effect that the physical layout of the processing area has on system response. The complexity of the casting operation necessitates the use of an integrative approach. The two models have very different objectives, formulations, and data requirements.

The attractiveness (and necessity) of using an optimization model to generate solutions for presentation to the simulation model is three-fold. First, producing feasible solutions manually based on expert knowledge is a tedious process and subject to biased judgement that may result in duplicating previous layout inefficiencies. This was demonstrated through multiple attempts at optimization of a foundry layout by process experts at TA-55. Optimization of facility layout by computer simulation requires time-consuming iterations as processing inefficiencies and violation of constraints are discovered. It is impractical to perform a search of the solution space using a simulation model given the amount of time that is required to run even one configuration. Second, as explained in Section 7.1, an optimization model alone cannot adequately account for the interactions that produce radiation exposure.

Third, simulation models are useful in performing what-if analyses where operation and transportation times, resource allocations, and failure rates are modified to study the effects on system response. However, if the basic premise behind an optimal layout of a facility is altered, a complete rewrite of a simulation model is often required. For example, the layout of the foundry was optimized on personnel radiation exposures. If a subsequent decision was made to optimize the layout for process efficiency, the operating assumptions would change, and the resulting layout could be very different. An optimization routine is easily modified by changing the objective function and/or the contraints The simulation model remains intact.

Analysis of competing facility layout configurations based on different optimizing assumptions is facilitated using an integrative approach to modeling The methodology investigated in this dissertation can be applied to any complex operation where communication between processes or facilities is important. Whether the degree of interaction between operations directly affects costs or often non-quantifiable concerns such as safety, an optimal facility layout results in the most efficient use of the resources available.

7.3 Future Research

Assessment of risks associated with individual processes performed at a nuclear facility is an important aspect in designing the layout of an operation. The objective function of the QAP for the foundry seeks to minimize exposures by locating high exposure processes apart from one another. An alternative objective is to minimize the probability of loss or injury by locating processes having an inherently high degree of risk away from those processes that would compound the risk. Consider an glovebox containing a furnace where fire is an identifiable hazard and a second glovebox where combustible materials are routinely processed or stored. Placing these gloveboxes adjacent to one another might result in greater loss in the event of an accident than if they were separated.

Sage [41] defines risk as ...the statistical likelihood of being adversely affected by some potentially hazardous event. Thus, risk involves measures of probability and severity of adverse impacts. There are numerous hazards associated with glovebox operations in the foundry, each having an assigned probability of occurrence and severity of impact. Some of the more common accident scenarios are listed in Table 7.1.

Urban [49] incorporates Muther s SLP system [36] which uses subjective closeness ratings to account for qualitative factors such as safety and environmental

Table 7.1 Accident scenarios for the casting operation

Event	Severity	Probability
Glovebox breach	Low	Very High
Loss of ventilation	Moderate	Moderate
Fire	High	Low
Criticality	Very High	Very Low
Plenum breach	Moderate	Very Low
High exposure material present	Low	Very High

considerations into the formulation of the QAP (see 3.1.2). This multi-criteria approach produces a facility arrangement that locates operations based on proximity desirability. Closeness ratings are usually subjective measures, and in a practical sense, difficult to establish. Urban requires that Muther s linguistic closeness ratings, which range from absolutely necessary to undesirable, be assigned numerical values for incorporation into the QAP formulation. In a nuclear facility, where the implications of placing risky operations adjacent to each other far exceed undesirable, development of closeness ratings requires a more rigorous analysis.

7.3.1 Fuzzy Logic

The descriptors of the ranges of severity and probability of occurrence of the scenarios listed in Table 7.1, illustrate the vague and imprecise nature of assigning risk. Does the statement that there is an high probability of a breach in containment indicate a 75% chance or a 90% chance of occurrence? Fuzzy logic is concerned with quantifying and reasoning using natural language where descriptors are inexact. The notion behind fuzzy systems is the construction of membership sets onto which inputs and outputs are mapped. Degree of membership, μi, takes on a value on the real range [0.0, 1.0] where 0 indicates null membership and 1 is full membership. The premise behind fuzzy set theory is that control variables can belong to more than one membership set. The membership sets comprise the fuzzifier which converts crisp values to fuzzy values. The fuzzy values are processed by a rule base consisting of a series of IF-THEN statements that model reasoning by duplicating the decision process of experts . Boolean logic operators such as AND, OR, and NOT are used to form the antecedent and consequent portions of the rules which provides much flexibility in modeling the decision process. Every activated rule in the rule base generates a fuzzy output which is essentially a recommendation for action. The defuzzifier weights the output values and assigns a crisp output usually by the centroid method (for discrete elements) defined as:

$$\mathrm{I} = \frac{\sum_{i=1}^{n} \mu_i C_i}{\sum_{i=1}^{n} \mu_i} \tag{7.1}$$

7.3.2 Application of Fuzzy Logic for Risk Assessment

One method for incorporating fuzzy logic into hazards assessment is to construct three membership functions - probability of occurrence and severity as inputs, and risk as output. Figures 7.2, 7.3, and 7.4 illustrate the input and output fuzzy sets for the system.

In the fuzzy sets, triangular membership functions map the inputs, probability and severity, and output, risk to the following overlapping fuzzy sets: very low VL, low L, moderate M, high H, and very high VH.

Consider a case where the probability of an event occurring is .60 and the severity of that event is assessed as .5, the problem becomes one of determining the level of risk associated with the occurrence of the event. Figure 7.2 illustrates the degree of membership where a probability of .60 maps to $\mu M = .25$ and $\mu H = .09$. Similarly, a severity of .5 (in Figure 7.3) maps to $\mu M = .45$ and $\mu H = .05$. The recommended action is the output value that corresponds to $\mu=1$ in the linguistic set.

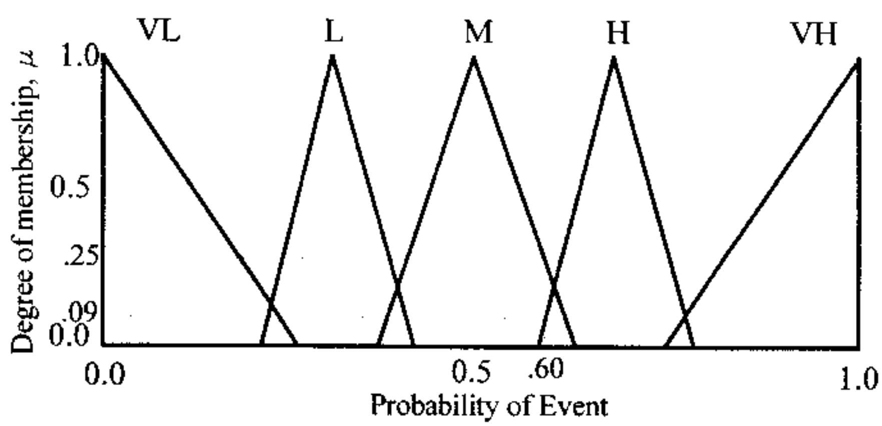

Figure 7.2 Fuzzy set for probability

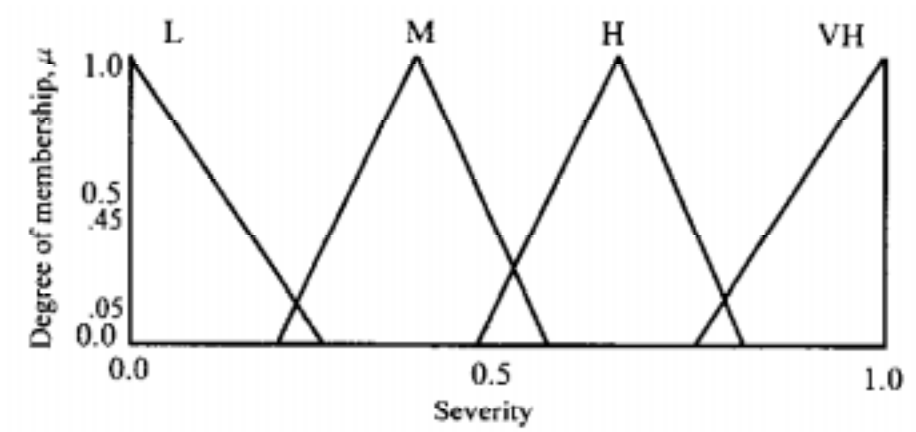

Figure 7.3 Fuzzy set for severity

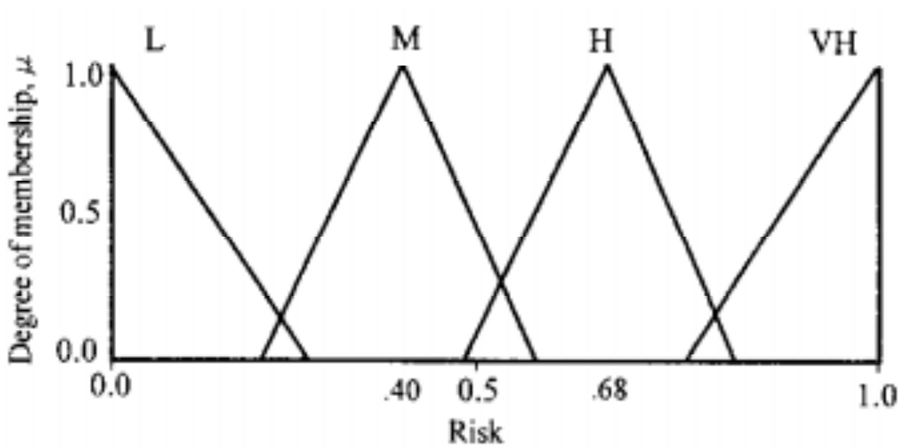

Figure 7.4 Fuzzy set for risk

For the output, risk, L = 0.0, M = 0.40, H = 0.68, and VH = 1.0. Table 7.2 defines the membership values of the the inputs as they are mapped to the linguistic sets.

Table 7.2 Membership values for input and output variables

μ_i	occurrence=.60	severity=.50
μ_{VL}	0.0	—
μ_L	0.0	0.0
μ_M	0.25	0.45
μ_H	0.09	0.05
μ_{VH}	0.0	0.0

A rule base consists of a series of rules depicting the causal relationships between the inputs and output. A sample rule base for this example is:

Rule 1: IF probability = very high AND severity = low THEN risk = moderate.
Rule 2: IF probability = moderate AND severity = moderate THEN risk = moderate.
Rule 3: IF probability = low AND severity = high THEN risk = high.
Rule 4: IF probability = very low AND severity = very high THEN risk = high.

The fuzzy input variables are presented to the rule base which produces a degree of membership for each rule. A crisp output is produced using the centroid method of Eq. (7.1). Table 7.3 summarizes the calculations.

Table 7.3 Calculating a crisp output value

	C_i	μ_O	μ_S	μ_i	$\mu_i C_i$
Rule 1	M = 0.40	VH = 0.0	L = 0.0	min{0.0,0.0} = 0.0	(0.0)(0.40) = 0.0
Rule 2	M = 0.40	M = 0.25	M = 0.45	min{0.25,0.45} = 0.25	(0.25)(0.40) = 0.10
Rule 3	H = 0.68	L = 0.0	H = 0.05	min{0.0,0.05} = 0.0	(0.0)(0.68) = 0.0
Rule 4	H = 0.68	VL = 0.0	VH = 0.0	min{0.0,0.0} = 0.0	(0.0)(0.68) = 0.0
output = 0.10 / (0.0 + 0.10 + 0.0 + 0.0) = 0.40 moderate risk					Total 0.10

7.3.3 Fuzzy Logic and the QAP

Every glovebox operation has an associated number of hazards (each with its own degree of risk). The summation of the individual risks represents the total risk for the process. A formulation of a QAP where the objective is to maximize the distance between hazardous operations or minimize overall risk is given by

$$\min \sum_{i=1}^{nprocs} \left[\frac{\sum_{k=1}^{nprocs} \sum_{r=1}^{nrisks} r_{ikr}}{dist^2(a_i, a_k)} \right] \tag{7.2}$$

The resulting solution procedure for the QAP integrates a fuzzy logic paradigm for risk assessment with a genetic algorithm containing a fitness function that minimizes risk. The GA seeks to locate adjacent processes in a manner that reduces the hazards associated with the casting operation. The simulation model can then determine the impact that alternative layouts have on performance measures for the foundry.

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APPENDIX A

RESULTS FOR PRIMARY PERFORMANCE MEASURES

Solution 1

Replication	Castings Produced	Background Exposure (mRem)
1	53	22.49
2	55	20.60
3	53	25.38
4	54	26.06
5	52	22.88
6	53	22.89
7	49	17.87
8	50	18.66
9	60	25.88
10	57	21.68
11	52	23.23
12	51	24.33
13	54	20.65
14	57	17.64
15	50	24.59
16	55	26.92
17	54	21.25
18	49	19.61
19	52	20.86
20	56	28.75
mean	53.30	22.61
variance	8.22	9.44
std dev	2.87	3.07

Solution 2

Replication	Castings Produced	Background Exposure (mRem)
1	59	27.83
2	49	25.69
3	55	28.05
4	53	28.33
5	54	27.66
6	53	26.99
7	53	26.60
8	52	27.95
9	55	29.12
10	56	26.54
11	56	27.31
12	54	27.57
13	56	28.75
14	55	27.67
15	55	28.93
16	52	28.30
17	52	27.18
18	53	28.49
19	51	28.70
20	52	28.49
mean	53.75	27.81
variance	4.93	0.80
std dev	2.22	0.89

Solution 3

Replication	Castings Produced	Background Exposure (mRem)
1	51	28.76
2	52	26.54
3	54	30.88
4	50	27.84
5	56	26.01
6	53	26.02
7	54	31.63
8	54	29.74
9	52	27.83
10	53	24.98
11	55	29.69
12	56	23.18
13	57	31.85
14	56	32.85
15	52	27.35
16	56	30.46
17	60	33.40
18	57	28.28
19	53	27.47
20	56	26.57
mean	54.35	28.57
variance	5.92	7.39
std dev	2.43	2.72

Solution 4

Replication	Castings Produced	Background Exposure (mRem)
1	57	29.93
2	57	25.10
3	53	25.66
4	55	28.29
5	49	26.53
6	58	26.77
7	50	31.30
8	58	22.98
9	51	25.00
10	49	25.65
11	50	23.92
12	54	27.59
13	52	29.26
14	50	25.61
15	56	29.70
16	55	25.62
17	56	31.18
18	53	26.71
19	52	27.75
20	56	32.43
mean	53.55	27.35
variance	9.31	6.72
std dev	3.05	2.59

Solution 5

Replication	Castings Produced	Background Exposure (mRem)
1	56	17.44
2	55	20.97
3	54	18.53
4	57	20.13
5	53	19.97
6	54	19.05
7	54	21.49
8	52	18.59
9	57	19.28
10	58	20.97
11	50	22.12
12	53	20.50
13	53	18.44
14	57	18.71
15	56	19.02
16	58	19.60
17	53	20.40
18	54	16.65
19	55	21.42
20	53	16.75
mean	54.60	19.50
variance	4.57	2.38
std dev	2.14	1.54

Solution 6

Replication	Castings Produced	Background Exposure (mRem)
1	52	25.66
2	54	27.07
3	53	27.25
4	54	25.86
5	54	26.52
6	55	27.54
7	50	28.64
8	51	26.28
9	55	26.92
10	54	26.52
11	50	25.71
12	52	24.33
13	55	25.38
14	55	28.65
15	56	27.32
16	55	24.14
17	53	24.45
18	58	27.01
19	56	24.82
20	53	26.39
mean	53.75	26.32
variance	4.20	1.68
std dev	2.05	1.30

Solution 7

Replication	Castings Produced	Background Exposure (mRem)
1	55	18.74
2	49	16.72
3	55	24.15
4	52	19.38
5	57	20.94
6	57	17.60
7	54	23.84
8	51	17.35
9	52	19.85
10	52	17.22
11	53	18.76
12	56	17.60
13	55	17.50
14	58	19.70
15	56	22.49
16	56	18.99
17	49	16.64
18	55	17.22
19	54	17.69
20	52	19.02
mean	53.90	19.07
variance	6.62	5.00
std dev	2.57	2.24

Solution 8

Replication	Castings Produced	Background Exposure (mRem)
1	53	21.34
2	53	15.59
3	55	24.93
4	55	16.86
5	49	16.85
6	52	18.85
7	54	20.31
8	52	17.59
9	55	18.97
10	58	24.17
11	55	25.55
12	56	17.35
13	57	23.34
14	55	17.32
15	54	17.75
16	53	19.37
17	54	21.13
18	54	22.22
19	55	26.40
20	54	22.98
mean	54.15	20.44
variance	3.71	10.78
std dev	1.93	3.28

Solution 9

Replication	Castings Produced	Background Exposure (mRem)
1	55	24.59
2	55	22.66
3	52	22.72
4	55	21.90
5	55	22.63
6	57	19.96
7	53	18.69
8	54	26.90
9	57	21.32
10	53	19.73
11	53	22.01
12	54	22.45
13	54	23.09
14	53	22.39
15	52	23.61
16	54	23.14
17	51	19.00
18	59	23.22
19	53	26.27
20	53	21.86
mean	54.10	22.41
variance	3.67	4.40
std dev	1.92	2.10

Solution 10

Replication	Castings Produced	Background Exposure (mRem)
1	58	18.36
2	50	17.31
3	55	17.25
4	53	16.76
5	52	16.46
6	55	18.83
7	50	16.84
8	51	16.82
9	52	16.00
10	51	17.81
11	57	18.25
12	53	19.78
13	48	19.30
14	50	18.46
15	55	17.96
16	54	16.98
17	56	20.12
18	55	19.06
19	57	16.96
20	58	18.40
mean	53.50	17.89
variance	8.68	1.33
std dev	2.95	1.15

APPENDIX B

RESULTS FOR BACKGROUND EXPOSURES WITH ADDITIONAL REPLICATIONS

	Solution				
Replication	10	5	8	9	1
1	18.36	17.44	21.34	24.59	22.49
2	17.31	20.97	15.59	22.66	20.60
3	17.25	18.53	24.93	22.72	25.38
4	16.76	20.13	16.86	21.90	26.06
5	16.46	19.97	16.85	22.63	22.88
6	18.83	19.05	18.85	19.96	17.87
7	16.84	21.49	20.31	18.69	18.66
8	16.82	18.59	17.59	26.90	25.88
9	16.00	19.28	18.97	21.32	21.68
10	17.81	20.97	24.17	19.73	23.23
11	18.25	22.12	25.55	22.01	24.33
12	19.78	20.50	17.35	22.45	20.65
13	19.30	18.44	23.34	23.09	17.64
14	18.46	18.71	17.32	22.39	24.59
15	17.96	19.02	17.75	23.61	26.92
16	16.98	19.60	19.37	23.14	21.25
17	20.12	20.40	21.13	19.00	19.61
18	19.06	16.65	22.22	23.22	20.86
19	16.96	21.42	26.40	26.27	28.75
20	18.40	16.75	22.98	21.86	22.89
21		22.63	26.47	21.08	23.76
22		22.67	19.48	23.75	26.34
23		18.51	19.10	20.34	18.38
24		19.24	23.65	23.86	16.34
25		21.93	13.30	26.04	23.12
26		18.49	19.07	21.69	22.83
27		17.54	20.98	17.85	27.76
28		20.99	19.38	22.07	18.52
29		17.98	20.28	20.57	27.60
30		18.56	23.79	20.99	22.42
31			24.86	21.10	20.39
32			22.86	24.62	18.72
33			19.84	19.76	19.67
34			20.73	19.59	22.18
35			20.48	26.61	23.34
36			19.31	20.98	25.40
37			21.15	19.58	17.87
38			19.53	22.96	19.58
39			23.61	24.31	20.50
40			19.24	23.64	17.53

	Solution				
Replication	10	5	8	9	1
41			26.06	22.59	19.10
42			21.40	19.84	19.73
43			26.45	20.37	28.80
44			15.90	23.36	20.75
45			18.91	21.73	21.61
46			20.89	26.62	21.32
47			19.48	21.44	18.79
48			21.79	22.07	21.89
49			19.03	22.27	19.17
50			19.27	22.83	24.94
51			20.35	23.01	25.81
52			18.81	22.59	23.46
53			26.11	22.06	28.03
54			20.49	21.88	25.69
55			26.47	23.76	20.01
56			28.09		18.66
57			21.79		20.42
58			19.73		19.88
59			16.93		18.62
60			19.27		21.09
61			16.01		22.03
62			16.86		23.47
63			24.37		22.28
64			20.41		23.07
65			21.39		22.34
66			14.35		24.07
67			17.33		26.37
68			23.25		20.52
69			20.31		24.05
70			23.11		27.60
71			22.15		20.80
72			22.38		21.70
73			19.17		22.64
74			19.14		18.33
75			20.28		21.18
76			17.79		19.49
77			20.58		19.33
78			20.68		17.05
79			23.82		17.18
80			17.95		20.48

			Solution		
Replication	10	5	8	9	1
81			17.89		23.90
82			22.36		24.74
83			23.77		22.02
84			18.18		17.80
85			19.60		22.41
86			21.39		26.53
87			21.37		19.58
88			22.36		22.31
89			21.11		22.68
90			25.68		25.48
91			16.69		33.27
92			23.89		20.87
93			17.89		23.68
94			17.19		23.79
95			14.59		21.51
96			21.79		18.26
97			20.25		22.92
98			16.20		17.93
99			23.33		26.64
100			23.25		23.16
101			18.58		20.09
102			20.82		18.98
103			16.21		18.02
104			23.41		21.82
105			18.02		27.78
106			19.93		18.46
107			23.41		22.21
108			21.23		26.77
109			20.94		20.84
110			23.09		24.12
111			18.62		22.40
112			22.18		18.57
113			19.03		22.23
114			24.42		19.44
115			16.26		17.93
116			17.75		25.46
117			22.50		28.52
118			15.73		
119			23.14		
120			17.74		

			Solution		
Replication	**10**	**5**	**8**	**9**	**1**
121			16.48		
122			22.87		
123			21.57		
124			27.93		
125			18.96		
126			22.42		
127			19.60		
128			19.94		
129			24.46		
130			19.68		
131			24.92		
132			18.93		
133			15.74		
mean(n_0)	17.88	19.50	20.44	22.41	22.61
variance(n_0)	1.33	2.38	10.78	4.40	9.44
std dev(n_0)	1.15	1.54	3.28	2.10	3.07
mean(Ni - n_0)		19.85	20.63	22.22	22.04
variance(Ni - n_0)		3.98	8.96	4.04	10.49
std dev(N_i - n_0)		1.99	2.99	2.01	3.24
W_1	1	1.33	0.3	0.72	0.34
W_2	0	-0.33	0.7	0.28	0.66
mean(N_i)	17.88	19.39	20.57	22.35	22.23

APPENDIX C

RESULTS FOR SECONDARY PERFORMANCE MEASURES

Solution 10

Replication	Total Exposure (Rem/worker)	Total Transport Time (minutes)	Time in System (minutes) Rods	Type A	Type B	% Utilization Worker	Material Preparation	Density
1	1.14	2308	3913	14703	26465	73.22	72.66	15.05
2	1.14	2286	3225	15788	25837	75.35	74.09	14.46
3	1.15	2305	3601	15438	25227	74.88	73.78	15.02
4	1.14	2226	3406	14057	22005	73.32	73.90	13.41
5	1.15	2222	3151	14051	24645	73.2	74.16	13.15
6	1.16	2344	3612	14451	29919	76.52	73.69	15.49
7	1.15	2270	3626	14184	20802	73.53	73.77	14.63
8	1.15	2268	3275	14452	23181	74.07	74.15	13.88
9	1.14	2219	3110	15319	20548	72.6	73.71	12.61
10	1.14	2249	3225	14778	21871	73.41	73.09	14.13
11	1.16	2314	3779	15357	22652	74.13	74.31	15.34
12	1.15	2291	3517	15243	25422	74.97	73.68	14.81
13	1.17	2269	3292	14418	31124	76.69	74.49	14.88
14	1.14	2286	3475	14039	22912	73.6	72.70	14.29
15	1.16	2340	3263	14993	25579	75.06	73.59	15.01
16	1.15	2299	3241	15155	23197	73.73	73.29	14.65
17	1.16	2363	3540	14733	29165	76.22	73.48	16.17
18	1.16	2324	3118	14765	30167	75.22	73.99	14.92
19	1.16	2316	3329	14636	23544	76.1	73.86	15.01
20	1.16	2295	3413	13841	24197	74.94	74.16	14.65
mean(20)	1.15	2290	3406	14720	24923	74.538	73.73	14.58
var(20)	8.71E-05	1616.80	49702.42	2.96E+05	9.71E+06	1.51	0.24	0.69
stddev(20)	9.33E-03	40.21	222.94	543.73	3116.72	1.23	0.49	0.83

Solution 5

Replication	Total Exposure (Rem/worker)	Total Transport Time (minutes)	Time in System (minutes) Rods	Type A	Type B	% Utilization Worker	Material Preparation	Density
1	1.15	1939	3426	14912	19714	72.83	73.82	14.03
2	1.16	1951	3458	13911	26566	75.42	73.29	14.89
3	1.16	1996	2978	14689	28877	76.1	73.97	16.15
4	1.17	1957	3634	14308	22681	74.11	74.64	14.89
5	1.15	1965	3142	15250	22758	73.83	73.24	15.01
6	1.16	1973	3585	15176	28206	73.94	73.96	15.66
7	1.15	1965	3070	14830	29215	75.1	73.11	14.81
8	1.14	1941	3418	13677	27039	73.45	73.73	14.04
9	1.15	1962	3201	14050	23587	73.21	73.46	15.34
10	1.16	1958	3595	14537	28259	74.77	73.95	15.30
11	1.16	1943	3562	13687	26881	72.11	74.78	14.13
12	1.16	1936	3287	14410	20264	72.26	73.86	13.50
13	1.15	1956	3274	14609	22073	74.25	73.36	14.68
14	1.16	1944	3178	15079	21541	75.86	73.69	14.11
15	1.16	1969	3256	14872	26005	75.68	74.29	15.11
16	1.15	1946	3630	14849	21676	75.67	73.09	14.64
17	1.15	1961	3362	14306	26326	74.25	73.45	15.01
18	1.14	1945	3473	14747	20436	72.89	73.33	13.98
19	1.15	1941	3203	14574	21095	73.15	73.47	14.45
20	1.14	1929	3238	14878	22148	76.12	73.19	13.82

Solution 5 (cont.)

21	1.16	1973	3507	16032	31500	76.46	73.76	15.20
22	1.16	1975	3471	15018	27567	77.12	73.88	15.48
23	1.15	1937	3911	14537	21038	73.03	72.82	14.34
24	1.15	1945	3892	14023	28305	75.27	73.23	14.54
25	1.15	1970	3520	15364	23820	75.68	73.20	15.15
26	1.14	1958	3024	14985	22030	73.89	72.97	14.67
27	1.15	1940	3719	14596	22019	73.84	73.71	14.26
28	1.15	1948	3583	13582	27239	72.85	73.69	14.42
29	1.15	1953	3532	14112	22837	74.69	73.69	14.48
30	1.16	1961	3320	14267	21886	74.42	73.98	14.93
mean(20)	1.15	1954	3348	14568	24267	74.25	73.68	14.68
var(20)	6.61E-05	244.99	37967.65	2.12E+05	1.02E+07	1.66	0.23	0.45
stddev(20)	8.13E-03	15.65	194.85	460.60	3199.05	1.29	0.48	0.67
mean(10)	1.15	1956	3548	14652	24824	74.73	73.49	14.75
var(10)	4.00E-05	185.11	68402.63	5.17E+05	1.26E+07	1.99	0.16	0.17
stddev(10)	6.32E-03	13.61	261.54	719.02	3553.38	1.41	0.40	0.42
mean(30)	1.15	1954	3415	14596	24453	74.41	73.62	14.70
var(30)	5.62E-05	219.06	55253.70	3.01E+05	1.07E+07	1.76	0.21	0.35
stddev(30)	7.50E-03	14.80	235.06	548.70	3270.29	1.33	0.46	0.59

Solution 8

Replication	Total Exposure (Rem/worker)	Total Transport Time (minutes)	Time in System (minutes)			% Utilization		
			Rods	Type A	Type B	Worker	Material Preparation	Density
1	1.16	1900	3337	14909	25113	74.4	73.74	15.11
2	1.12	1866	3331	13995	22197	72.13	72.68	13.41
3	1.16	1898	3433	16300	21516	74.79	73.38	14.80
4	1.16	1883	3471	14445	22187	75.12	73.67	14.56
5	1.15	1862	3770	14585	19508	73.64	73.74	13.47
6	1.15	1891	3294	13492	24335	74.78	73.88	15.03
7	1.17	1915	3508	14503	24574	75.76	74.54	15.24
8	1.15	1877	3772	14093	27535	74.64	73.92	14.31
9	1.16	1880	3435	14591	22108	74.16	73.98	14.07
10	1.15	1898	3498	14504	26591	72.93	72.39	14.88
11	1.17	1930	3093	14839	31252	77.32	73.79	15.59
12	1.14	1884	3180	15027	21147	74.49	73.03	14.65
13	1.16	1882	3223	15975	24239	74.89	73.37	14.43
14	1.15	1867	3422	14108	21260	74.35	73.55	14.15
15	1.14	1887	3505	15639	24134	74.6	72.86	15.13
16	1.14	1880	3607	14241	24088	77.08	73.44	14.72
17	1.17	1903	3800	14251	25257	72.77	74.46	15.20
18	1.16	1899	3271	13821	26047	73.58	73.87	14.89
19	1.16	1903	3251	15176	28820	74.65	74.12	14.38
20	1.16	1885	3352	14844	25583	74.25	74.41	13.79

Solution 8 (cont.)

21	1.17	1942	3099	15357	34093	77.38	73.49	16.46
22	1.16	1898	3179	14535	25112	73.08	74.04	15.20
23	1.15	1884	3283	14720	21265	76.5	73.55	14.99
24	1.16	1892	3399	14777	26911	74.4	73.23	14.87
25	1.13	1823	3782	14735	20197	73.25	73.55	12.44
26	1.14	1876	3208	15490	23965	73.85	73.07	13.64
27	1.15	1852	3449	14228	22740	72.66	73.61	13.18
28	1.14	1863	3601	14101	23528	74.2	73.39	13.95
29	1.15	1880	3314	14536	26576	75.99	73.75	14.68
30	1.16	1906	3778	13733	26872	76.47	73.54	15.61
31	1.16	1929	3340	15365	28154	75.12	73.85	15.91
32	1.16	1897	3584	12627	28894	75.66	73.87	15.34
33	1.16	1887	3357	15117	23911	73.63	74.04	14.21
34	1.16	1883	3424	14561	27757	75.46	74.24	14.29
35	1.17	1925	3119	14711	25424	76.31	74.31	15.95
36	1.15	1871	3189	16333	20029	74.47	73.62	13.65
37	1.16	1907	3541	14146	26097	76.58	73.35	15.20
38	1.14	1862	3711	15484	22028	74.31	73.59	13.97
39	1.15	1898	3652	13989	24821	74.2	73.51	15.22
40	1.15	1887	3483	14096	25215	73.43	73.31	14.56
41	1.17	1918	3422	15399	28927	75.32	74.17	15.29
42	1.16	1906	3354	14677	24528	74.8	73.91	15.12
43	1.17	1906	3145	15281	29695	75.3	73.64	15.52

Solution 8 (cont.)

44	1.13	1861	3412	15294	18178	72.17	73.09	13.59
45	1.14	1894	3493	14662	25267	74.68	72.99	14.45
46	1.15	1881	3438	13571	26947	73.81	73.98	14.25
47	1.16	1896	3294	14676	22918	74.06	74.25	14.56
48	1.16	1885	3561	13635	24732	74.69	74.36	14.51
49	1.16	1899	3716	12883	24968	74.66	72.84	15.60
50	1.15	1864	3258	14150	23332	74.62	74.19	13.96
51	1.15	1878	2991	15754	22799	75.05	73.52	14.26
52	1.15	1892	3789	14515	22797	75.76	73.42	15.29
53	1.17	1913	3373	14847	31902	74.45	74.08	14.89
54	1.14	1898	3735	14503	22996	74.76	73.33	14.97
55	1.16	1923	3595	14368	33795	76.36	73.61	15.61
56	1.17	1935	3733	14619	32603	76.62	73.59	16.07
57	1.16	1902	3676	14018	25053	75.17	73.48	15.89
58	1.14	1857	3683	14678	21915	75.8	73.51	13.57
59	1.15	1862	3589	14910	18839	73.83	74.11	14.15
60	1.15	1872	3448	14512	22748	73.7	73.37	14.15
61	1.15	1837	3347	13999	19333	74.01	74.43	13.39
62	1.14	1884	3561	14472	21344	74.29	73.19	14.34
63	1.15	1905	2849	15708	27912	78.28	73.30	14.46
64	1.16	1919	3450	14455	25210	76.15	74.33	16.10
65	1.15	1871	3411	14170	26165	72.72	73.53	13.86
66	1.13	1832	3766	14468	18937	71.76	73.26	12.66
67	1.14	1857	3148	14261	20565	72.11	72.89	13.65

Solution 8 (cont.)

68	1.15	1900	3302	14041	30206	74.85	72.89	15.13
69	1.16	1887	3436	13963	26127	75.3	73.07	14.97
70	1.15	1919	3474	14781	26724	75.8	73.45	15.27
71	1.14	1894	3341	14177	31250	76.2	72.79	14.98
72	1.15	1896	3529	14770	25636	74.16	72.99	14.66
73	1.13	1889	3590	14991	23208	74.52	72.47	14.87
74	1.15	1889	3147	14452	25243	74.99	73.92	14.70
75	1.15	1874	3207	16245	21477	76.07	73.47	14.06
76	1.15	1895	3629	15535	23417	76.4	73.75	14.57
77	1.15	1882	3180	15578	27385	73.6	73.67	14.11
78	1.17	1891	3290	15252	23182	74.02	74.13	14.80
79	1.17	1933	3301	14666	29811	75.03	74.47	16.22
80	1.13	1847	3307	13798	19519	74.19	72.99	12.62
81	1.16	1901	3285	15453	27583	75.64	74.10	14.87
82	1.16	1907	3013	15400	25575	74.41	74.04	14.95
83	1.14	1909	3809	14616	26392	74.92	72.71	15.41
84	1.15	1875	3551	15207	21549	74.17	73.56	14.47
85	1.15	1869	3507	15166	24334	73.16	73.85	14.15
86	1.16	1890	3582	14714	29195	75.62	73.88	14.58
87	1.17	1916	3361	14407	30849	76.19	74.59	15.66
88	1.17	1875	3665	15065	23479	74.13	74.98	14.40
89	1.15	1897	3615	15673	26480	74.09	73.73	14.97
90	1.18	1940	3474	14349	32318	75.63	74.03	16.68
91	1.14	1886	3249	14362	21881	74.92	73.44	14.48
92	1.16	1878	3894	14542	24754	73.93	73.69	14.17
93	1.15	1892	3341	14700	22040	74.94	74.22	14.90

Solution 8 (cont.)

94	1.14	1891	3621	15379	24296	74.31	73.53	14.69
95	1.15	1863	3386	14139	20999	76.85	74.16	13.58
96	1.16	1911	3355	14011	24829	73.05	73.45	15.21
97	1.16	1850	3855	15190	22978	74.93	74.33	13.35
98	1.15	1867	3592	14669	20878	75.39	73.80	14.20
99	1.16	1916	3352	14556	25357	75.23	73.14	15.59
100	1.15	1898	3720	15290	25855	74.03	73.11	15.07
101	1.16	1905	3590	14576	23676	75.21	74.00	15.09
102	1.15	1875	3474	14427	24525	74.65	73.36	14.69
103	1.15	1901	3071	14443	23787	74.57	73.07	14.87
104	1.15	1882	3351	14121	26589	74.49	73.84	14.08
105	1.15	1897	3411	14400	25155	77.69	73.79	14.84
106	1.16	1861	3485	14518	25528	74.03	73.97	13.47
107	1.15	1907	3295	15103	32216	75.93	73.25	14.44
108	1.15	1913	3584	14696	27160	75.84	73.13	15.63
109	1.16	1884	3094	14855	24699	75.23	74.05	14.54
110	1.15	1890	3142	14235	27977	75.09	73.61	14.86
111	1.15	1893	3679	14388	25869	75.71	73.71	14.85
112	1.15	1905	3296	14642	26372	75.39	73.19	15.07
113	1.15	1892	2949	14753	26549	77.44	73.09	14.80
114	1.16	1922	3531	14562	27163	75.81	73.50	16.31
115	1.15	1878	3818	13942	18365	72.83	73.72	14.02
116	1.17	1919	3490	14055	24442	76.65	74.27	15.86
117	1.17	1913	3089	15819	28438	75.79	74.19	15.54
118	1.13	1859	3680	14340	23114	73.84	73.05	14.13
119	1.15	1878	3211	14711	25836	75.04	73.48	14.08

Solution 8 (cont.)

120	1.15	1884	3541	14480	21519	73.55	73.83	14.51
121	1.15	1885	3520	14211	21708	72.7	73.21	14.80
122	1.14	1898	3099	14980	29154	76.68	73.01	14.47
123	1.14	1880	3080	15480	24320	75.65	73.22	13.78
124	1.17	1925	3276	14778	33033	73.95	73.55	15.81
125	1.15	1896	3348	14058	24220	72.81	73.30	14.17
126	1.15	1901	3275	14626	26560	75.34	73.72	15.32
127	1.14	1876	3340	14705	25055	74.66	73.25	13.94
128	1.16	1869	3435	14981	24581	73.76	74.21	13.89
129	1.16	1933	3523	13464	26031	73.89	73.67	16.17
130	1.16	1874	3404	14046	23991	74.17	73.91	13.91
131	1.14	1872	3147	14464	21499	99.05	72.68	13.57
132	1.16	1874	3609	14412	23691	73.78	74.11	14.20
133	1.15	1881	3237	15903	20583	73.13	73.75	13.72
mean(20)	1.15	1889	3428	14667	24375	74.52	73.64	14.59
var(20)	1.52E-04	278.05	38850.60	4.99E+05	8.13E+06	1.57	0.33	0.35
stddev(20)	1.23E-02	16.67	197.11	706.74	2850.49	1.25	0.58	0.59
mean(113)	1.15	1890	3423	14650	25099	75.02	73.62	14.67
var(113)	1.10E-04	518.22	47710.08	3.81E+05	1.15E+07	6.72	0.22	0.69
stddev(113)	1.05E-02	22.76	218.43	617.39	3389.92	2.59	0.47	0.83
mean(133)	1.15	1890	3423	14652	24990	74.94	73.63	14.65
var(133)	1.15E-04	479.75	46076.61	3.95E+05	1.10E+07	5.96	0.23	0.64
stddev(133)	1.07E-02	21.90	214.65	628.77	3314.75	2.44	0.48	0.80

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