Small Modular Nuclear Reactors: Parametric Modeling of Integrated Reactor Vessel Manufacturing Within A Factory Environment Volume 2, Detailed Analysis

Xuan Chen, Arnold Kotlyarevsky, Andrew Kumiega,
Jeff Terry, and Benxin Wu
Illinois Institute of Technology

Stephen Goldberg and Edward A. Hoffman
Argonne National Laboratory

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This study continued the work, supported by the Department of Energy's Office of Nuclear Energy, regarding the economic analysis of small modular reactors (SMRs). The study team analyzed, in detail, the costs for the production of factory-built components for an SMR economy for a pressurized-water reactor (PWR) design. The modeling focused on the components that are contained in the Integrated Reactor Vessel (IRV). Due to the maturity of the nuclear industry and significant transfer of knowledge from the gigawatt (GW)-scale reactor production to the small modular reactor economy, the first complete SMR facsimile design would have incorporated a significant amount of learning (averaging about 80% as compared with a prototype unit). In addition, the order book for the SMR factory and the lot size (i.e., the total number of orders divided by the number of complete production runs) remain a key aspect of judging the economic viability of SMRs. Assuming a minimum lot size of 5 or about 500 MWe, the average production cost of the first-of-the kind IRV units are projected to average about 60% of the a first prototype IRV unit (the Lead unit) that would not have incorporated any learning. This cost efficiency could be a key factor in the competitiveness of SMRs for both U.S. and foreign deployments.

DISCLAIMER

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I. Overview

By Dr. Robert Rosner

The paper is the fourth in a series of papers prepared by the Institute discussing the economic issues pertaining to future nuclear deployments. This paper focuses on the learning process for small modular reactors (SMRs).

In November 2011, we published a technical paper that analyzed the economic and financial aspects of SMRs and suggested policy options regarding incentivizing SMRs ("Small Modular Reactors – Key to Future Nuclear Power Generation in the U.S." Available at https://csis.org/files/attachments/111129_SMR_White_Paper.pdf.)

Nuclear power continues to offer the potential as a major worldwide, scalable, carbon-free energy source; if the challenges of safety, nonproliferation, waste management and economic competitiveness are addressed.

It is believed that small modular nuclear reactors (SMRs) may be able to increase the size of the commercial nuclear reactor market by providing a smaller financial barrier to entry. However, little work on SMRs has focused on the industrial engineering aspects of the SMR industry. The goal of this study is to analyze in detail the learning for the production of factory built components contained within the Integrated Reactor Vessel (IRV) of an SMR. The study participants recognize that new approaches in industrial modeling practices could provide further insights into the learning process.

II. Research Plan

The research team consisted of experts at the Illinois Institute of Technology (IIT), including faculty members (materials, industrial engineering, and nuclear engineering) and two graduate students with expertise in industrial modeling simulations. The study team performed this activity in four stages: (1) detailed literature review of the manufacturing and installation practices of these allied industries to identify specific analogs for use in the modeling of SMR manufacturing; (2) consultation with experts in nuclear energy consulting practices both domestically and internationally; (3) development of generic SMR design; and (4) simulation of the manufacturing.

III. Introduction

The new Gen III+ reactors now under construction have been designed to maximize economy of scale [Goldberg, 2011]. Though the reactors are constructed on-site at the final location, each reactor is identical and makes use of modular construction techniques that enable the prefabrication of some components prior to installation. The current belief is that the use of factory produced components and identical building techniques will reduce the cost of these large scale reactor builds [Smallman, 2011]. Even with these projected cost savings, the large scale (1100 MW) reactors are expected to cost on the order of $7-8 billion each. These are large capital outlays for any US utility [Goldberg, 2011].

There are many utilities that cannot afford such capital costs, but that would like to use nuclear plants to reduce carbon emissions[Deutch, 2003][White, 2000]. One proposed method for reducing costs while still expanding a utility's nuclear footprint is to utilize smaller reactors that can be built using modular techniques[Rosner, 2011]. Several of these smaller scale reactors could be built on a single site as needed to meet demand[ITA, 2011]. A staggered construction schedule allows the costs to be spread over a much longer time period. If these smaller reactors could be factory built an even greater savings, due to economy of mass production, could be realized. A new class of Small Modular Reactor (SMRs) [Borchardt, 2010] has been been proposed to allow this paradigm to be attempted.

On December 1, 2011, the Energy Policy Institute at Chicago (EPIC) issued publicly two white papers, "Small Modular Reactors – Key to Future Nuclear Power Generation in the U.S,"[Rosner, 2011] and "Analysis of GW-scale Overnight Capital Costs."[Goldberg, 2011] The EPIC team conducted an extensive analysis of the economics of both gigawatt (GW)-scale reactors and small modular reactors (SMRs). The SMR white paper provided the business case and a business plan for SMRs, including recommendations regarding future research. The SMR white paper [Rosner, 2011] identified several issues, including: (1) the size and pace of the investment in and the throughput and tooling up requirements of a mass manufacturing; (2) improved understanding of the learning rates[Wright, 1936], including the appropriate application of analog learning data and analysis for capital and operations and maintenance (O&M) costs from other allied industries; and (3) the application of advanced manufacturing [NSTC, 2012] techniques that could reduce the overall investment requirements for the SMR fleet.

This work focused on the first two issues identified in the EPIC SMR white paper[Rosner, 2011]. Here, the project team studied the cost drivers for factory built components of small modular reactors, using advanced analytic tools[SEER, 2011] in nuclear engineering, industrial engineering, and cost estimating. These tools allowed the team to develop an economic analysis for the factory build components within the integrated reactor vessel (IRV) of SMRs[IAEA,2011], with emphasis on manufacturing techniques at the factory; efficient and effective operations and maintenance practices that lead to learning; and the lot size necessary to minimize inefficiencies in the manufacturing process for a fleet of small modular reactors.

A. Scope

This project was designed to assess the cost drivers of the emergent SMR manufacturing industry. It was beyond the scope of this work to assess any particular design. Therefore, the inherent reliance on automation (smartness of design) was assumed to be high. With the assumption that the manufacturing would rely on automated manufacturing as often as possible, the cost drivers of manufacturing were to be used to determine if mass production and vertical integration could reduce manufacturing costs in the SMR industry. If a reduction was observed, the cost drivers were to be used to estimate the rate of cost reduction with the number of units produced (learning curve) and to determine the minimum number of orders (lot size) that would be required to maintain a true factory economy of scale. This was accomplished by ascertaining the knowledge that could be credited by the industry, parametric modeling of the factory built components of the SMR, designing a generic 100 MWe SMR, and identifying a set of parameters that would be appropriate for use in an SMR modeling.

i.) Developing the SMR Generic Model Parameters

The initial task of the project was to determine a set of modeling parameters that were applicable to SMR manufacturing[GAO, 2009]. Central to this initial effort was an extensive literature review focused on manufacturing processes, construction practices, and labor rates of allied industries deemed to share critical characteristic similarities (regulatory, safety, materials handling, personnel requirements, etc.) with the forthcoming SMR manufacturing industry. The following allied industries have been considered: aircraft manufacturing, naval manufacturing, conventional power generation (nuclear and fossil), the semiconductor manufacturing, the food industry, and the alternative energy industry (solar and wind). These analogous systems were assessed to develop an understanding of the nature of manufacturing, labor, and learning rates in large scale manufacturing industries.

The data mined from the analog industries allowed the team to develop parameters that were used to model costs[Balasubramanian, 2011] associated with the manufacture of SMRs. The literature search targeted charge out rates[Bilek, 2007], cost of materials, manufacturing techniques and efficiencies learning rates, quality control, tooling requirements, and project management. Two important areas of analysis from the literature search involved understanding the efficiencies that could be gained by large-scale manufacturing and estimating learning rates for the specific types of work involved in SMR construction. These issues will differ depending upon the type and magnitude of work that is currently performed in existing factories, and that will be performed in a factory setting for the SMR industry. However, the literature values for the allied industries provide for a means to benchmark the predicted data from the parametric modeling of SMR manufacturing. The analog data identified in the literature was analyzed and used to develop input parameters for the parametric model of the 100 MWe SMR.

ii.) Designing a Generic 100 MWe SMR

The scope of this project did not include cost estimation of a specific SMR design and the team did not have access to detailed design specifications or machine drawings from any SMR vendor. It was necessary to have a generic design that could be used as a starting point for the parametric analysis. Fortunately, there are constraints placed upon the SMR designs that limit the range of possibilities [DOE, 2011].

Two constraints largely limit the designs of small modular nuclear reactors. The SMRs must utilize factory built components that are transportable (typically, by rail or truck) and the designs must be licensable[DOE, 2011] by the U. S. Nuclear Regulatory Commission. The requirement that the SMR plants be licensable in the short term caused the team to focus on SMRs utilizing Light Water Reactor

(LWR) designs. The existing SMR vendor market was assessed and the designs of those vendors using LWR technology were compared to determine the viability of developing a generic SMR design.

The intent of the announced SMR vendors is to use factories to manufacture and assemble the modular reactors central to SMR power plants. The problem of shipping large reactor parts to the final site for installation necessitated considerable redesign of existing reactor components. Specifically, this transportation requirement has constrained the size of most SMR components to that of a rail or road shipment. These redesigns aimed at accommodating the limits of rail/highway transport do not rule out the possibility that more complete reactor parts could be shipped by barge to further reduce costs. However, the limiting factor is the size of rail and highway tunnels. Reviewing the LWR–based SMR designs [Welter, 2010][Westinghouse, 2011][Babcock, 2012][Holtec, 2012] made it clear that the transportation constraint required all of the designs to have similar attributes. The team drew upon these similarities to establish a generic 100 MWe SMR design used in the parametric modeling study.

iii.) Parametric Modeling of a Generic 100 MWe SMR

The modeling performed here focuses on the factory built components of the Integrated Reactor Vessel (IRV). The IRV contains the nuclear reactor core, control mechanism, coolant pumps, steam generator, and pressurizer. To be clear, the generalized design was not a blueprint for building a fully functional IRV. It represents an idealized IRV which captures the essential systems; essential as defined by not only function, but also in terms of contribution to the overall cost of production. The parametric modeling of the SMR and SMR subsystems was performed by separating the IRV into a set of separable components using method-specific manufacturing processes.

The parametric modeling utilized the cost estimation software, SEER-MFG[SEER, 2011]. The cost estimates were developed from a parametric model of the product and production process. Each of the main elements of the IRV was treated as a separate entity, and was separately broken down and examined as individual components with different processing or purchasing requirements. Identification of how the individual components are fabricated and assembled determines the materials/parts, labor, and tooling that go into making that part. The individual components are combined into the completed IRV.

Once the simulation on a LEAD IRV were completed, the process was further refined using Monte Carlo techniques [Ulam, 1947][Metropolis, 1949][Goldberg, 2003] on each component in the model. The simulations yielded detailed cost estimates addressing the main cost drivers involved in SMR production in terms of labor, materials, design, tooling, and the expected effects of learning on the cost reduction.

iv.) Crediting Knowledge in the SMR Manufacturing Industry

The SMR industry will not emerge in a vacuum. There is a large amount of preexisting process knowledge in many of the manufacturing techniques[JSW, 2012] that will be utilized to build the SMR IRV. Certain components such as the fuel assemblies are designed to be off-the-shelf commercially available[Ray, 2010][WNA, 2012]. Also, more component manufacturers can provide parts due to the smaller designs with passive safety features in the SMRs[Babcock, 2012a]. While it is likely that many SMR manufacturers will purchase many off-the-shelf components, the model used in this study was initially set up with most parts being assembled in the SMR factory. This was done to make the model as flexible as possible. This flexibility will allow future refinement by replacing existing components with more sophisticated designs or purchased parts. It also allowed for the parametric model to credit prior process knowledge.

The SMR industry must receive some credit for the expected reduction in cost but will face a subsequent reduction in learning as well. The developed parametric model and simulations lay the foundation for investigating the degree to which knowledge credited to existing commercial industries will affect the SMR manufacturing industry. Despite the absence of an existing SMR factory, many of the SMR components will be based on technology that has already undergone some degree of maturation. The parametric model was updated based upon the understanding of preexisting learning. This updated model was used to determine the costing parameters and learning curves of the First–of –a–Kind (FOAK) and Nth–of–a–Kind (NOAK) plants. The resultant model provides more accurate estimates of expected SMR production costs and learning curves. These models provided the basis for determining the size of a lot that is necessary to ensure that the SMR factory remains operating under optimal conditions.

v.) Determining the Effect of an Order Book

In order for the SMR factory to function in an optimal manner, there must be enough orders to keep the factory at full operations for a given staffing level. There are benefits to full operation to both the vendor and the customer. It is clear that downtime in the factory increases the costs to the manufacturer. Full operation, however, benefits customers as well, especially the early customers. Lot average costing [Goldberg, 2003] is a method for spreading the costs of development and tooling over many production items. Due to learning[Wright, 1936], the later production items usually have reduced costs as compared to the first production units. In the nuclear industry, this can lead to no utility wanting to purchase the FOAK plant to avoid paying these development costs. By guaranteeing that a solid order book exists, lot average costing can be used to spread these development costs among a group of purchasing utilities. The parametric model was used to determine the minimum size of the initial order that provides this benefit and still protects against the real possibility of an order cancellation. Under ideal conditions the first IRV units would not be produced until the number of orders met or exceed the minimum order book size.

The lot size for efficient manufacturing was optimized by conducting Monte Carlo modeling of the SMR production. The calculated SMR IRV cost was compared to the number of orders of SMR components to be manufactured by the SMR vendor factory along with the calculated learning rates. Simple regression formulas allowed for the determination of the minimum number of orders needed to maximize the benefits gained from the factory production of SMR IRVs. These estimates relied upon the parametric modeling and Monte Carlo capabilities of SEER–MFG[SEER, 2012][Stump, 2012] which will be described below.

B. Methodology

Before the modeling process can be described it is necessary to define certain terms that the team has used in the parametric modeling. It is necessary to describe the language of learning that we will use in this paper as learning rates and progress rates are often used interchangeably. Also, the concepts of combining the production of individual components into lots or orders must be described to avoid confusion.

i.) Order Size vs Lot Size

The manufacture of the SMR components is simulated in terms of the production of separate batches of components. These batches are called “lots.” A functional definition for a “lot” is number of units produced before any major changes to the manufacturing process are initiated [Goldberg, 2003]. In a factory setting, it is impossible to continuously implement lessons learned throughout the manufacturing process. Rather, reorganization of fabrication systems, factory layout, and product redesigns must be triggered at the beginning of the next production run, or at some other major break in production, to least disrupt the flow of manufacturing[Goldberg, 2003]. It should be noted that the NRC design certification will restrict flexibility in altering the actual design from lot to lot. It is expected that the vendor will, however, have the flexibility to alter how it goes about manufacturing the approved design. For a given component, the number of units produced between two such instances is the size of the lot. There are no physical restrictions on the size of a lot. A factory may decide to never institute any changes of this kind and therefore, all of the units produced by this factory belong to one lot. Conversely, a factory may decide to make changes between every unit produced, rendering each unit produced its own lot.

Lot sizes are a distinct quantity from order size. An order represents a cumulative list of components necessary to complete a final product. An order may be for only one completed product, but one complete product could consist of many smaller units, or require several lots of of some other unit for its completion. As will be explained in greater detail below, each IRV requires multiple coolant pumps and a single pressure vessel [Westinghouse, 2011]. The coolant pumps and pressure vessels may be manufactured in lots of any size, but the minimum number of coolant pumps and pressure vessels necessary to complete one IRV represents an order size of one. This is an important distinction because a quantity of interest is the initial order book; the number of orders an SMR factory needs, at the outset, to maximize the benefits of learning within a factory setting.

ii.) Learning Rate vs Progress Rate

One of the central quantities of interest when considering the economics of SMR manufacture is the rate at which the production cost will diminish over time. This phenomenon was given the term “learning”[Wright, 1936] for historical reasons, but learning is actually the result of many separate factors whose combined effect is to reduce the cost of production[Oswalt, 1991]. For a detailed discussion of learning refer to Appendix B, only a short description of learning rates follows. Though many differing learning models exist[Goldberg, 2003], this work utilized log-linear, continuous learning models similar to those proposed by T. P. Wright in his landmark 1936 paper.

Learning models, like the Wright model, can be plotted as straight lines on a double-log plot[Wright, 1936][Stewart, 1995]. The slope of these lines is a quantity directly related to the amount of learning, and referred to as the learning slope (b). The learning slope relates the log of the unit number to the log of the average cost of that unit number[Dahlhaus, 1967]. Mathematically, the learning slope can be expressed as[Goldberg, 2003]:

$$b = \frac{log(TC(2x)/TC(x))}{log2} \qquad \text{Eq. 3–1}$$

Here, TC(x) refers to the total cost of producing the xth unit. Similarly, TC(2x) refers to the total cost, per unit, of producing the doubled unit. This ratio is referred to as the learning rate, and is frequently expressed as a percentage. A learning rate of 100% means that no learning has taken place because the total cost of the doubled unit is the same as the total cost of the x^{th} unit. A learning rate of 50% means that the total cost of the doubled unit is half of the total cost of the x^{th} unit. The learning rate describes the cost of production as a percentage of the prior cost upon doubling the number of units produced. Quite confusingly, the term “learning rate” is often used interchangeably[Gumerman, 2004] with a quantity known as the “progress rate” which is simply one minus the learning rate[Margolis, 2002]. Therefore, a learning rate of 100% corresponds to a progress rate of 0%, and a learning rate of 50% corresponds to a progress rate of 50%[Rubin, 2004]. The progress rate is a measure of the cost reduction upon doubling the number of units produced. To avoid any confusion, this work utilized the standard mathematical notation of learning rates and the correlative percentage, rather than the progress rate and the complementary percentage.

iii.) SEER Modeling

Modeling techniques for a spectrum of production scenarios and learning rates of SMRs were developed, where LEAD, FOAK, and NOAK critical reactor structures were derived by the study team for the reactor pressure vessel and reactor core internals which form the Integrated Reactor Vessel (IRV). This was accomplished by performing analyses[Goldberg, M. T., 2003] of the manufacturing processes, materials, and learning effects through computer simulations. This process begins by a careful breakdown of the nuclear power plant, starting with the most general systems descriptions then deconstructing these systems into increasingly simple constituent parts. Whenever possible, this process terminates in a part that can simply be purchased at a known price. However, as SMRs incorporate novel components, this process often necessitates a breakdown into the raw materials and fabrication that make up the parts that cannot be purchased [Zakarian, 2006]. The manufacturing processes are fortunately very well understood. Costs for techniques such as casting, machining, welding, molding, etc. are based on some combination of the material, labor, and tooling demands, which are well known for both domestic and foreign sources[Anderson, 2009]. All costs were based upon U. S. domestic manufacture of all of the SMR components. The final result was a full accounting of the materials, manufacturing processes, tooling, and labor necessary to produce a generic LEAD SMR[Hogue, 2012]. The model was further refined to determine the costs of a FOAK and NOAK.

The second phase of the analysis was the determination of the learning curves. In order for the learning curve models for SMR production to converge quickly, good starting estimates of the learning curve slope were needed[Goldberg, 2003]. A range of starting estimates for the FOAK plants were developed within a range set by adjusting labor, material, and tooling estimates from the allied industries to the nuclear industry. These values were used to populate the initial parameters of the SMR learning curve models. Using the results from the LEAD SMR and the allied industry parameters, learning curve simulations generated projections about the long term production costs of SMRs as well as the order size necessary to efficiently manufacture these SMR components. The model has been set up to allow further refinement as more information becomes available (such as full machine designs of a plant).

This will allow exploration of parameters that can be optimized to to reduce production costs and improve learning curves over the production lifecycle [Heemstra, 1992] of the SMR IRV.

The cost estimates and learning curves were generated using the cost estimation software − SEER–MFG[SEER, 2011]. The cost estimates are developed from a parametric model of the product and production process. SEER–MFG allows each of the main elements of the IRV to be treated as a separate entity, and to be separately broken down and examined as individual work elements. This process was repeated at all levels of the product design, from the largest component to the testing of an individual weld. The individual work elements were determined by the following characteristics: their physical separability, the production process, and assembly. A work element was either a purchased part, a raw material, or a singular structure treated as an individual component. Though certainly not a requirement, the physical size was reduced to the smallest components. Once the work elements were determined, the next step was to determine the size, shape, materials used, production process, and assembly. Most production processes were reduced to some combination of the following: casting, forging, machining, welding, heat treatment, chemical treatment, electrical work, cladding, or physical assembly. Record keeping and non–destructive testing were also accounted for in each stage of production. Each of these operations was characterized by differing time scales, labor rates, and learning rates. By supplying SEER–MFG with the data on components, materials costs, labor rates, the production processes, non–destructive testing, and a rough design detailing the dimensions and weight of the work element, it was possible to generate projections for the total labor, materials, tooling cost, production time, and ultimately, the learning rates for construction of the IRV of a small module reactor. To put the learning rates of the IRV into context, a summary of the learning rates of allied industries is presented.

C. Learning Curves of Allied Industries

Prior to the development of the parametric models, cost estimates, and learning curves for the SMR, it was necessary to build a data set that would be the basis for the investigation and model building process. A key component of this data set consisted of a comparative analysis of the relevant allied industries. The industries studied were selected along the criteria of regulatory environment faced, technology utilized, or manufacturing techniques employed by the allied industry. One of the quantities of chief concern is the nature of learning curves in these industries. Specifically, how learning is measured and reported, and what learning rates are typically achieved in these industries. A more detailed account of the literature review concerning the allied industries can be found in Appendix A, but a brief summary of the results (Table 3-1) of this investigation are detailed below.

i.) Aircraft

The manufacture of airframes, and aircraft in general, is a highly complex process employing many of the methods a potential SMR industry would necessarily use. It is also highly regulated by the Federal Aviation Administration[FAA, 2013]. The resultant products are similar in construction to SMRs including large metal structures that have been welded together. These flying pressure vessels must be designed to withstand the stresses of operation. The use of a dedicated factory setting, a high degree of automation, technical and logistical sophistication, and regulatory constraints create a legitimate basis for comparison with SMR manufacturing. The aircraft manufacturing industry has the distinction of being the first industry to be analyzed with learning models, with a historical learning rate of 80%

[Wright, 1936]. In the intervening years, this learning rate was corroborated, however, this was conditional on certain manufacturing practices which diverge from the SMR production processes being considered[Archian, 1950][Benkard, 2000]. Specifically, existing aircraft factories produce multiple models of aircraft at one time using the same facilities and personnel. These inconsistencies with the proposed nature of an SMR factory, and manufacturing specifics such as the balance of materials, provides grounds for some skepticism of the parallels between learning rates expected in SMR production and aircraft manufacture[Defense, 2012][Goldberg, 2011].

ii.) Shipbuilding

Modern shipbuilding yards are designed around the principle of modular construction[Smallman, 2011]. The shipbuilding industry has demonstrated that products as complex as a nuclear submarine can be assembled from a finite number of prefabricated modules[Defense, 2012]. This makes the shipbuilding industry relevant to the study of SMRs as modularity is central to the SMR concept. Additionally, shipbuilding yards are highly specialized, dedicated facilities with highly skilled labor requirements as would be expected to be utilized by SMR vendor factories. This similarity would be reflected in the structure of recurring versus non-recurring costs in SMR and ship manufacture [Defense, 2012][Goldberg, S., 2011]. The shipbuilding industry also has been at the forefront of area based design and integration, block material purchases, detailed planning, strong program management, and early stakeholder involvement. These areas will likely be fertile grounds of potential knowledge transfer for the SMR industry. Learning in the shipbuilding industry is frequently modeled using Wright's learning model with observed learning rates between 80-85% [Stump, 2012].

iii.) GW-Scale Reactors

One might expect that GW scale nuclear facilities would be a sound analogy to SMRs. Of the main U. S. SMR vendors, all use pressurized light water reactor technology[Welter, 2010][Westinghouse, 2011][Babcock, 2012][Holtec, 2012]. This is the same technology that is used in nearly two-thirds of U. S. fleet of active nuclear reactor power stations[NRC, 2013]. Many of the structures currently in use in GW-scale reactors are only slightly modified or even unaltered in numerous SMR designs. To develop the parametric model of the manufacture of an SMR, the construction techniques implemented in the GW-scale reactor industry have been closely studied. In particular, the Westinghouse AP1000 reactor pressure vessel was taken to be a nearly direct analog of the pressure vessels used in SMR designs. However, due to the intermittent development of nuclear power in the United States, the industry has failed to develop a continuous production schedule and therefore attempts at characterizing the learning curve for GW–scale nuclear reactors have been inconclusive [DOE, retrieved 2012]. Studies even suggest that there may even be negative learning in the GW–scale industry[Grubler, 2010]. Therefore, it is difficult to draw conclusions on the expected learning from GW scale reactors, although it is expected that the modular construction used in the new reactor designs will improve the utility of this analog [Garver, 2010]. For example, there are 2 AP1000 reactors currently under construction within the US. The early cost data on the construction indicate that the first plant at the Vogtle site is running approximately $1B over budget[Southern 2012], while the second plant at SCANA's V. C. Summer plant is reported to be nearly $300M under budget due to lessons learned from Vogtle and China [Nuclear 2012]. It will be interesting to observe how learning in the modular AP1000 construction progresses. At the moment, though, the two point trend suggests that learning will be positive.

iv.) Semiconductors

Semiconductor manufacturing was investigated as a possible analog of SMR manufacturing due to commensurate levels of complexity in the manufacturing process, the need for highly skilled labor, the strict internal regulations, the need for personnel and property protection, and the consistency of production. The semiconductor fabrication process requires hundreds of steps performed in a clean room environment by automated machines and highly skilled workers. This system is designed to maximize the effects of learning and to reduce inefficiencies which serves as an excellent analogue for a dedicated SMR factory. However, in semiconductor manufacture, many different models with multiple generations of each model are concurrently produced. This is in stark contrast with the proposed SMR vendor factory, where only one generation of one model is produced at a time. A complete account of learning in the semiconductor industry must take into account these multiple generations and multiple models. However, over short time periods, and focusing on single models, a learning rate of 80% was observed using traditional learning models[Irwin, 1996].

v.) Photovoltaics

Photovoltaics are produced using similar techniques as those found in the semiconductor industry. The industry has a high degree of internal regulation to ensure the consistency and quality of the product. This serves as an analog for off-the-shelf suppliers. Photovoltaics also have the quality of being a competing technology in the alternative energy market. One major problem for the photovoltaic-SMR analogy results from the complete lack of consensus on learning within the photovoltaic industry. According to a survey of the various attempts at determining the photovoltaic learning rate, the learning rate has been observed to vary between 53-83%[NEEDS, 2006][Brinkerhoff, 2012]. In some observed cases[NEEDS, 2006], the learning rate in photovoltaic production was not constant and large reductions of cost were observed likely due to major technological advances before flattening out again. This large spread in learning rates due to discontinuous manufacturing advances limits the applicability of comparisons between photovoltaic and SMR industries.

vi.) Wind Turbine Generators

The technological sophistication, physical scale, and relation to the problem of power generation made the manufacturing of wind turbines an excellent choice for allied industry. The production of wind turbine generators is a strong analogy for the manufacture of large, complex, materials intensive components. Wind turbines make use of many exotic materials[Alonso, 2012] which may be relevant to the SMR industry. The wind turbine manufacturing industry commonly makes use of the Wright [Wright, 1936] model in estimating learning curves. Using the standard models, data exists which shows the learning rates of production and installation is between 90-96% [NEEDS, 2006]. Also, there are data which show a dependance on power output, these models yield a learning rate of 88% [Coulomb, 2006]. The lack of agreement is not a serious concern, as these values serve as a general indicator of the real learning curve. They also indicate that modern manufacturing in the nascent wind energy factories are higher than observed historically in the other industries. This has implications for the SMR industry where learning may be expected to be similar to wind manufacturing rather than older more human reliant manufacturing plants. Intuitively, the wind turbine generators seem to be the most representative of factory IRV manufacturing.

vii.) Food Service Industry

The food service industry was studied as an allied industry for the insights into expected learning rates for highly manual production operations. The typical tasks performed by any food service contractor are related to serving and replenishing food, setting and clearing tables, sanitizing facilities and equipment, food preparation, handling foods, supplies, and equipment, maintaining the grounds of the assigned buildings, maintaining the food service equipment and quality-controlling the quality of the services provided. All work must conform to pre-established standards of performance and is regulated by local health departments. Prior to starting work, contractor personnel receive instruction in the principles and practices of food services sanitation given by the base medical services personnel. Each of these separate operations serves as an analog to some manual operation performed either inside the SMR vendor factory, or on the final job site. A study of learning within the food service industry showed that the learning rates fell between 85-98%[Reis, 1991]. This study raised the issue that these learning rates were consistent over short periods of time, i.e. 6 months, and that learning among manual operations drops significantly. This casts doubt on one of the underlying assumptions built into many common learning models, that learning is continuous and unlimited.

D. Conclusion

The details of SMR economics and learning will be based largely on the simulations of the interplay between the materials, production methods, labor, and tooling involved in the manufacture of the components of the generic SMR design. This study presupposes a dedicated, specially built vendor factory as the setting for the bulk of the manufacturing processes, as well as the availability of domestically sourced materials, off-the-shelf parts, and labor[Rosner, 2011]. These assumptions are crucial to the application of the methodology detailed in the previous sections, and form the foundation for the parametric model building, and costing of the generic SMR design. The literature review yielded some initial values for expected learning, as well as production methods, and labor rates, that will inform the construction of the parametric models [Wright, 1936][Welter, 2010][Westinghouse, 2011][Babcock &Willcox][Miroyannes 2006][Irwin, 1996][Brinkerhoff, 2012][Coulomb, 2006][Reis, 1991] that were used in the modeling described in the rest of this report. Now it is possible to begin the task of building the generalized SMR design and cost estimates and comparing the predictions to those of allied industries.

IV. Generalized IRV LEAD Cost Estimates

One of the central goals of this study was to examine the rate of learning to be expected in the production of the IRV of an SMR. The learning rate is important because the both the total cost and the size of an order needed to maintain a factory manufacturing environment depends upon these learning curves. It is not possible to determine the rate of learning without having a model with defined systems that rely on parameters that can be varied to determine the change in cost with production unit number. This section describes the starting design for the Integrated Reactor Vessel (IRV) of a LEAD SMR from which to explore the cost drivers. In order to develop the initial IRV, it was required to explore the proposed designs of the SMRs. Proposed SMR designs are very diverse with a wide variety of features including power output, cooling system, and fuel type[Hinze, 2012]. The team developed a design for the IRV used in the modeling by setting specific simplifying conditions. First, all phases of production would take place in a specialized factory environment and the factory, as well as all sources of raw materials and purchased parts, would be based in the United Sates. Regional labor costs were not considered but may be adjusted within the model in future studies. Second, the cost of building the vendor factory, as well as any other non–recurring costs were not considered. Third, a path to licensing was required of the design. Fourth, detailed schematics would not be available for a potential design. While detailed schematics[Oswald, 1991] would allow for refinement of the cost estimate of the production of the IRVs, it is not necessary to understand the cost drivers for planning purposes. Within the bounds of these constraints, a design for the IRV of the SMR was developed for use in the parametric model. What follows is a description of the parameters that were central to the modeling of the production of the generalized SMR IRV. The level of detail reflects the image of the IRV as interpreted by SEER-MFG[SEER, 2011]. Thus, the information is conveyed to best represent the level of detail required by SEER to build the cost estimates. Results for all of the subcomponents of the IRV of the LEAD SMR will be discussed in detail only in this section. Further sections will focus on the cost drivers of the complete IRV.

A. Model Parameters

The SEER–MFG software reports the modeled components in terms of the cost of: labor, materials, tooling, and other (purchased components and redesign)[SEER, 2011]. These cost drivers define the economics of an industry based on the manufacture of a product. The cost of labor was determined by taking supplied hourly labor rates and applying these to the total number of hours worked on each components. The cost of materials was determined by the types of materials used and their respective cost, and multiplying this by the amount of each material is used. The cost of tooling was calculated from the amount of material processed, the manner in which a part was fabricated, and the complexity of the process used in the fabrication. Finally, the other costs were largely determined by cumulative costs of the purchased parts used in the manufacture of the IRV. The input parameters for the model were dependent upon the labor rates; materials quantity and cost; tooling; and the individual reactor components and the associated manufacturing processes needed for each component.

i.) Labor Rates

The labor charge out rate was the cost of employing a single employee which includes the hourly wages of that employee as well as ancillary costs such as payroll tax, benefits to the employee (i.e.

health insurance), insuring the employee against accidents at work, etc. This implies that the labor rates varied by profession. This implication is supported by the data compiled by the Bureau of Labor Statistics [Bureau of Labor Statistics, 2011]. The labor rate for a welder will be different that those of an engineer. Though, the way in which the labor rates vary was not necessarily obvious. For instance, a welder does not need as much schooling as an engineer, and so the hourly wages reflect this difference. However, engineers are at less risk of having heavy machinery fall on them while on the job; therefore, insuring an engineer costs less to the employer. Labor rates also vary by industry [Bureau of Labor Statistics, 2011a]. This reflects the inherent complexity, risk, and other factors which separates industries. An electrician working on a nuclear submarine will be more costly to employ than an electrician working in an office building. Therefore, the two primary concerns of determining the labor rate are the profession and the field.

To determine the relevant labor rates used in this simulation, the manufacturing process was reduced to the operations necessary to fabricate the components. Each of the components of the generalized SMR IRV were produced by some combination of machining, welding, forging, casting, cladding, and heat treating, setup, and assembly. There is also a large effort need for quality control and non–destructive testing. These operations were the most labor intensive, the most costly, and were the most closely associated with the implicit costs of the SMR industry. It is possible to add more types of operations and refine the simulation as machine drawings of IRV components become available. However, in the context of IRV fabrication, these other operations would constitute a tiny fraction of the overall work performed and were already partially captured within the extensive fabrication library in SEER–MFG [SEER, 2011]. This library includes labor rates for many industries, and conveniently, these labor rates are broken down by process and profession. Because the goal is to simulate SMR manufacture, and that the chief technology being employed is that of nuclear energy, fabrication should use the labor rates of the nuclear manufacturing industry. Unfortunately, the SEER library did not have the labor rates for nuclear manufacturing built in, and this data was not immediately available elsewhere. Therefore, it was necessary to interpolate the labor rates.

The labor rates were approximated by correlating available labor rate data in a closely related industry to the nuclear industry labor rates. The aerospace industry was selected as an analog for the determination of labor rates. The basic relationship between the labor rates of the differing manufacturing processes is believed to similar to that which is expected in a nuclear manufacturing industry. Using the labor rate archive built into SEER, the labor rates for aerospace manufacturing processes were obtained. The main obstacle to the direct application of these labor rates is that these rates represent the environment produced by the aerospace industry. To attempt to replicate the environment produced by the nuclear manufacturing industry, there needed to be a means of relating the two industries in a way that captured the underlying complexity of each industry. It is the belief of the team that the engineering in these two industries, in part, captures the relative complexity of each field. By taking the ratio of the wage rates of these two professions, a proportionality constant is obtained which can be used to correlate the labor rates of these two industries. This correlation is represented by Equation 4-1:

$$NuclearOperationLaborRate = \frac{NuclearEngineeringWages}{AerospaceEngineeringWages} * AerospaceOperationLaborRate \qquad \text{Eq. 4-1}$$

The mean hourly wages of nuclear engineers and aerospace engineers are tabulated by the Bureau of Labor Statistics, and are known to be \$71/hr and \$49/hr respectively[BLS2, 2012]. With these values, as well as those in the SEER library, it was possible to better approximate the labor rates present in nuclear technology manufacturing. The results of these calculations are tabulated in Table 4-1.

	Welding	Machining	Forging	Casting	Assembly	Setup
Aerospace	\$130	\$130	\$110	\$110	\$135	\$135
Nuclear	\$190	\$190	\$160	\$160	\$195	\$195

Table 4-1: Comparison of Hourly Rates Between Aerospace and Interpolated Nuclear IRV Manufacturing

One potential concern is the sensitivity of the model to the values listed in Table 4-1. If shipbuilding had been chosen as the basis for generating the nuclear labor rates, as opposed to aerospace, how much different would the cost be? If the mean hourly wage rate is any indication, ship engineers earning \$36/hr [Bureau of Labor Statistics, 2012] would indicate that the absolute labor rates would be greater than those listed in Table 4-1. If it were true that the parallel between nuclear and aerospace engineering is a bad one, and that nuclear engineering would be more accurately compared to shipbuilding, then this would imply that the values in Table 4-1 would be an underestimate. An argument could be made that this suggests some need for testing the sensitivity of the model to these values. However, because this model is designed for use with the SMR industry, further refinements of the parameter space would almost certainly involve the real nuclear labor rates, rather than an estimate based on a comparison with an allied industry. At this point, these estimates serve to provide a reasonable starting point from which to begin modeling.

ii.) Materials

The materials used in the parametric modeling of IRV fabrication were obtained from the SEER catalogue of materials and material prices. These prices were spot checked against the market prices whenever possible. Generally, the agreement between the SEER price and the listed price was sufficiently close so as to trust the values given by SEER. The reluctance to use the market prices stems from the inherent volatility of the market price of materials like steel. It is not within the scope of this project to speculate on material prices. Therefore, the prices of the materials used in each component were input into the SEER model as exact parameters. The specific materials and material prices are detailed during the discussion of the fabrication of each IRV subcomponent.

iii.) Tooling

Tooling is composed of several related quantities including the cost of design; development; setup; fabrication of the tools; and the cost of replacing the consumable quantities [Maldonado, 2012]. The most commonly understood quantity associated with the term “Tooling” is that of the replacement of consumables. Consumables are items which are used during manufacture but do not contribute to the final IRV components. Examples of consumables include drill bits, gasses, wire used in welding, etc. SEER–MFG models the cost of the consumables from the size, weight, finish, and complexity of the various fabrication processes.

For any production process, the machines, assembly lines, workstations, and tools are determined by a research and development process which continues over the course of production. Even with the assumption that the vendor factory is dedicated to the manufacture of SMRs, fabrication and assembly are continually being refined. In the case of IRV manufacture, lessons learned from the completion of previous lots will be incorporated in the production of the following lots. An example would be the rearrangement of workstations in an assembly line because the original flow of production limited accessibility to some component. Similarly, some automated fabrication processes may utilize outdated machines that would be replaced with newer, better suited machines. Improvements of this kind are themselves a production process consisting of a design/redesign process and fabrication. A related contribution to the cost of tooling is the need for upkeep and periodic setup of the tools. An example of this is when a CNC milling machine is used for more than one operation. To transition from one operation to the next, the new program must be loaded and tested prior to resuming production. These costs were referred to as Tooling Labor and were calculated with the labor rate described above as setup.

B. Basis for the Generalized Design

The technology underlying small modular reactors was investigated to determine the potential SMR designs which are most likely to be licensable in the near future. There are many different methods of deriving power from nuclear fission [IAEA, 2006]. However, in the United States, all of the 99 operating nuclear power reactors utilizes a Light Water Reactor(LWR) design. Of these light water reactors, the overwhelming majority (65) of the reactors use Pressurized Water Reactors(PWR) technology[NEI, 2011]. While there are many interesting advanced designs from SMRs[Hinze, 2012], licensing considerations suggest the initial SMRs will be based upon PWR technology. This reality is reflected in the American SMR market. The companies that announced that they had competed for the $450M U. S. Department of Energy SMR Funding Opportunity Announcement were Nuscale, Generation mPower, Holtec, and Westinghouse [Licata, 2012]. These companies have SMR designs based upon PWR technology[Holtec, 2012][Welter, 2010][Westinghouse, 2011][Babcock &Wilcox, 2012]. To be relevant to the current SMR market, the generalized design implemented in this study was based upon a PWR.

In a PWR, nuclear fission[EIA, 2012] heats a primary coolant that is cycled in a closed loop between the reactor core and one or more steam generators [Kumar, 2001]. This loop is traditionally referred to as the Nuclear Steam Supply System (NSSS) [Achkasov, 1997]. The primary coolant enters the steam generator where it passes through a collection of small tubes before exiting the steam generator and returning to the reactor core [NIC, 2012]. The tubes inside the steam generator are submerged in water, the secondary coolant, which is turned to steam[Buongiorno, 2010][VNS, 2012]. The steam passes through the steam separators and dryers before being diverted to the steam turbine. The steam pressure turns the turbine which powers an electrical dynamo to generate electricity[VNS, 2012a]. The steam exits the steam turbine and enters a condenser which cools the steam back into water. The water is passed into a water treatment facility before finally being pumped back into the NSSS[USNRC, 2012].

SMR designs based upon PWR technology incorporate each of these systems. In a GW–scale reactor, the reactor core and steam generators are separate entities. Each exists in their own large containment vessel[Buongiorno, 2010]. The signature characteristic of the SMR designs is the nuclear reactor core, control mechanism, steam generator, and pressurizer are located inside a single containment vessel called an integrated reactor vessel (IRV)[Miller, 2012]. This consolidation comes at the expense of power output. To compensate for the reduced power output, a number of integrated reactor vessels can be located on a single site to generate a higher power output. An array of IRVs would be contained inside a concrete structure similar to those found in already existing nuclear power plants[Buongiorno, 2010], with the exception that it must accommodate the new technological form factor. Apart from this modification, the rest of the facility could be identical to an existing nuclear power plant. Any SMR power plant would necessarily include structures containing the steam turbines and generators, condenser, water treatment, water heater, pumps, control facilities, and other safety and backup systems [Gilbert, 2010].

A generalized SMR design begins with the integrated reactor vessel and then extends outwards to the rest of the facility. Therefore, the generalized design includes an IRV containing the nuclear reactor core, control mechanism, coolant pumps, steam generator, and pressurizer [IAEA, 2011]. The power output of the generalized IRV used in this modeling was fixed at 100 MWe. This value for the power output is consistent with the values found in the range of designs proposed by the main SMR vendors [McClure, 2012].

C. Components

The central defining element of many SMR designs is the so-called integrated reactor vessel (IRV) [KAERI, 2011]. Containing the PWR technology, the IRV is the source of superheated steam for the NSSS in the SMR power plant [WNA, 2012]. A discussion of the main components of the IRV, the constituent subsystems, their design, and their function in the IRV follows. Using SEER-MFG[SEER, 2011], the fabrication of the components was simulated based on the generalized design of the SMR IRV. These simulations were based upon the approximate size and weight of the component, the specific manufacturing processes necessary to manufacture the component, the relevant labor rates, the relative complexity of the manufacturing processes and their associated learning rates, the materials and their associated costs, and the nature and extent of testing being employed [SEER, 2011].

It is important to reiterate that the simulation software does not use machine drawings as the basis for the estimation. Rather, the size, weight, and complexity of the component stand in for the details normally contained in a blue-print. Therefore, detailed design specifics are not required for the purposes of the simulation. The relative complexity of the specific operations in a given manufacturing process are determined by the built in specifications of the SEER-MFG simulations or by utilizing currently known procedures. When creating a work element defining a component's production, in specifying that welding, machining, or some other process is a necessary step, a complexity standard was assigned. As a rule, when dealing with large components, or the assembly of many parts, the complexity, according to SEER-MFG, is considered to be highly complex, or very highly complex.

These estimates for the LEAD cost of the IRV components are the product of multiple simulations as produced by the parametric project management and cost estimation software, SEER-MFG[SEER, 2011]. Using the details of the generalized design, and ranges of values for various parameters (labor rates, material cost, etc.), SEER–MFG randomly generates a proposed production value for each component, and ultimately, the IRV. This is one Monte Carlo step. Each simulation consists of at least

1000 such steps, forming a normal distribution about some mean value [SEER, 2012a]. This mean value is the estimate for the LEAD cost. The cost estimates are divided into the cost of labor, the cost of materials, the cost of tooling labor and replacement, and other costs typically associated with purchased parts. The total cost of each component is represented as 100% and each of the cost drivers makes up a fractional portion of the total cost.

By utilizing the nature of the normal distribution, the standard deviation in the simulated distribution of components is calculated. This natural variation in the simulation provides an estimate on the error in the cost estimates. SEER-MFG provides the standard deviation in the total cost of a simulated work element, as well as the standard deviation in the labor required to fabricate that part. In the case of tooling replacement and other costs, the error is taken to be zero. This is because the costs of the purchased parts are input as fixed values obtained from a list price. The same is said for the parts needed for the component of the cost of tooling which is related to the replacement of consumables. The total error in the component cost was taken to consist entirely of the error in the materials, labor, and tooling labor costs, so by subtracting the error in labor cost and tooling labor cost from the total error, an *estimate* on the error in the materials cost was obtained.

The results of all simulations are listed to the 85% confidence level. The error is listed as a percentage of the cost of each cost component. For example, if the labor cost is listed as 43±3% of the cost of a component, the error indicates that the range of values for the labor cost as a fraction of the total component cost is between 40%-46%. Similarly, if the cost of an IRV component is listed as 34±1% of the total IRV cost, the actual cost contribution is between 33%-35%. The setup of each subcomponent of the IRV, materials, fabrication, and the results of the LEAD simulation are described in detail below.

i.) Pressure Vessel

The pressure vessel houses the internal systems of the IRV. It is designed to serve as both the external housing for these systems and as the coolant containment and pressure retainment structure [IAEA, 2007]. The outer structure of the pressure vessel is the physical barrier which maintains the primary and secondary coolants in the liquid phase. The primary coolant is heated to temperatures well in excess of 600°F [NEI, 2012], where under atmospheric conditions, the coolant would undergo a phase change and become a gas. As a coolant, gaseous water is considerably less efficient than liquid water [Lamarsh, 1975]. The pressure vessel serves to contain the high pressure necessary to maintain liquid water at these temperatures.

The IRV pressure vessel design was based on the general structure of the AP1000 reactor vessel, although it was modified to maintain consistency with the overall dimensions imposed by the SMR market. The reason for adhering to the AP1000 reactor vessel design is simple: the AP1000 is a design whose production process is understood. First, the AP1000 reactor vessel was designed to operate under conditions no less extreme than those expected for an SMR IRV [IAEA, 2007]. The operating conditions present in the AP1000 pressure vessel are nearly identical to those which existing SMR pressure vessels will be expected to withstand [IAEA, 2007][NEI, 2012]. Typical temperatures and pressures reached in an existing PWR pressure vessel, like the AP1000, are approximately 600F at 15MPa [IAEA, 2007]. Whereas, in an SMR, 608F and 14.1MPa are cited as typical operating conditions [IAEA, 2009]. Therefore, the basic design principles, and manufacturing process deployed in producing an AP1000 reactor vessel served as a guide for developing the pressure vessel of the generalized SMR IRV.

Using the existing SMR vendor market as a guide, the overall dimensions of the generalized SMR IRV were determined[Welter, 2010][Westinghouse, 2011][Babcock &Wilcox, 2012]. A number of similarities become apparent in the many different SMR designs that have been proffered. These similarities are a byproduct of the constraints imposed on the design. Specifically, most of the companies are planning to ship the IRVs by rail or flatbed truck. A limit is imposed upon the size of the IRV to that which can be transported using the available transportation infrastructure. This limitation is cited by NuScale, Westinghouse, and Generation mPower [Welter, 2010][Westinghouse, 2011][Babcock &Wilcox, 2012]. This restriction has produced a surprising degree of homogeneity in the designs for the integrated reactor containment vessel. Table 4-2 contains the power output and size of three potential SMR designs. The reactor containment vessels, despite the wide performance range provided by the designs put forth by NuScale, Generation mPower, and Westinghouse, are similar in size and weight. In other words, the consolidation of the IRV is driven by the "shippable" size. Therefore, the design for the pressure vessel in the generalized IRV used in the parametric model was taken to be 13 feet wide, 81 feet long, and with walls 8 inches in thickness; dimensions consistent with the 180-225 MWe SMRs which are appropriate for the model's 100 MWe SMR. The generalized design has 2 nozzles built into the sides to allow for the circulation of steam, and for the other electrical systems necessary to regulate the reactor core [IAEA, 1999]. It is understood that this is an oversimplification; the pressure vessel will likely have more penetrations. However, given the absence of detailed schematics indicating a more appropriate number of penetrations, two large openings in the pressure vessel were chosen to provide access for all electrical systems and steam systems.

The pressure vessel in the generalized IRV design was fabricated from SA-508 class II steel [NRC, 2012] consistent with the AP1000 design. Carbon steel was used for all parts of the pressure vessel because of its heat and pressure resistant properties [IAEA, 2009]. The material is extremely common and relatively easy to work. SEER-MFG[SEER, 2011] was chosen in part due to its extensive internal

	Thermal Power	Electrical Power	Length	Width	Weight	Fuel Core Configuration
NuScale	160 MW	45 MW	65'	14.5	400	U235 <5% 37* (17 X 17) 6' fuel rods
Generation mPower	530 MW	180 MW	83'	13'	628	U235 <5% 69* (17 X 17) 8' fuel rods
Westinghouse	800 MW	225 MW	81'	11.5'	280*	U235 <5% 89* (17 X 17) 8' fuel rods

Table 4-2: Key Parameters of Three SMR Designs [Welter, 2010][Westinghouse, 2011][Babcock &Wilcox, 2012].

library of materials with the updated prices and properties ready to be used in simulations. The approximate price for carbon steel was taken from the library as $1.65 per pound in 2013 US Dollars.

The basic design of the pressure vessel is that of a large, enclosed, pill-shaped container. This shape was created by combining in the model a semi-spherical top and bottom cap with three central ring sections [IAEA, 1999]. One of the ring sections contained two nozzles which allow for the circulation of the secondary coolant [NRC, 2012]. The top and bottom caps were forged from the ingots of carbon steel. The rough shapes were then machined to meet specifications. The ring sections were cast and then forged. Casting the ring sections is considered by the SEER guidelines to be a highly complex process, whereas the forging of the top and bottom caps is a very highly complex process. Figure 4-1 shows the general processes used to form pressure vessels, and illustrates some of the inherent complexity involved in manufacturing such large steel structures.

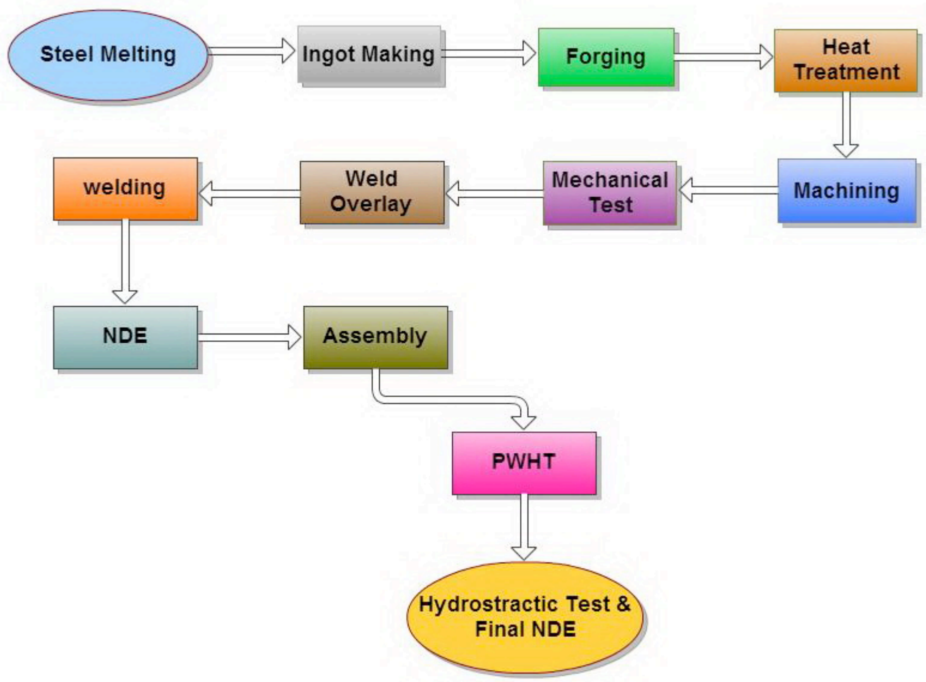

Figure 4-1: Fabrication Process for Pressure Vessel [JSW, 2012].

The forged rings were machined to specification before the being joined by welding [JSW, 2012]. Machining the large sections requires specialized, automated industrial machine tools that require extensive setup and programming before they can begin operations. This is considered to be a very highly complex process. Similarly, the welding is also taken to be very highly complex because of the size of the welds, and the need to meet very high quality standards. The ring containing the two nozzles was formed from ring segments, two of which contained the pre-cast, forged, and machined nozzles [IAEA, 2009]. These segments were formed into one complete ring by welding to form the ring with two nozzles. Once the top cap, bottom cap, and the ring sections were completed, they were setup for welding and joined into the completed pressure vessel. The final design weighed approximately 380 tons which is consistent with figures seen in the literature [Burgos, 2010]. Another relevant quantity to the SEER simulation is the surface area, which is a variable used to determine the extent of machining required. The surface area was determined to be approximately 5,500 ft^2. Finally, the pressure vessel was examined using nondestructive testing to ensure that the vessel was within the tolerances for pressure containment [Dobman, 2011].

The simulation results for the LEAD pressure vessel are presented in Figure 4-2 and Table 4-3. Materials costs were the dominant cost driver of the pressure vessel at 41 ± 1% of the total cost of the pressure vessel. Labor also was a significant driver at 31 ± 3% of the cost. The Monte Carlo simulations determined that the total error in this component was ± 6%. The costs of all NOAK (Nth-of-a-Kind) pressure vessels depend upon the parameters and fabrication techniques described here.

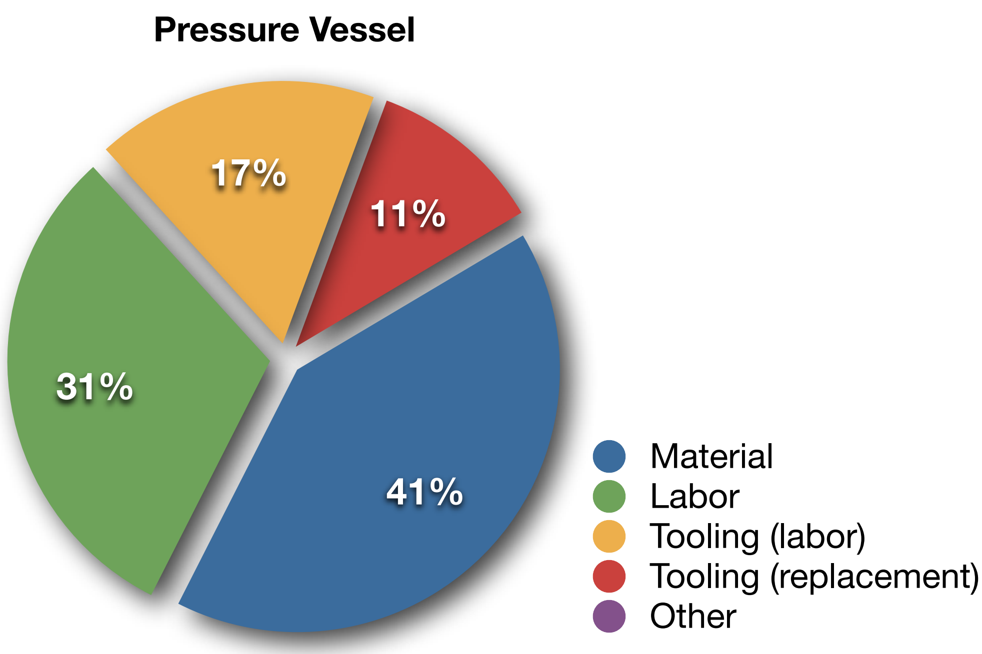

Figure 4-2: Production Cost Breakdown of Pressure Vessel by Cost Drivers

Cost Driver	% Cost of Component	Error as % of Total Component	Error as % of Total IRV
Material	41%	±1%	±1%
Labor	31%	±3%	±1%
Tooling Labor	17%	±2%	±1%
Tooling Replacement	11%	±0%	±0%
Other	0%	±0%	±0%
Total	100%	±6%	±3%

Table 4-3: Pressure Vessel: Cost Contribution and Error by Cost Center as % of Total Component Cost and IRV Cost

ii.) Nuclear Reactor Core

Heat is generated in the nuclear reactor core through the regulation of a nuclear chain reaction. The nuclear reactor core consists of bundles of fuel rods, each containing the nuclear fuel [Ray, 2010]. As the nuclear fuel decays, the nuclei spontaneously emit neutrons which trigger the decay of other nuclei in the vicinity, setting up a chain reaction [Lamarsh, 1975]. In the process, heat energy is emitted, which is absorbed by the coolant in which the fuel bundles are submerged. The reactor core in the generalized IRV design is consistent with the design specifications detailed in Table 4-2. Specifically, the 17 by 17 fuel rod assembly is the industry standard in practically all existing PWRs[NEI, 2004]. These fuel assemblies, or bundles, form the core of the reactor, and contain the fissile material

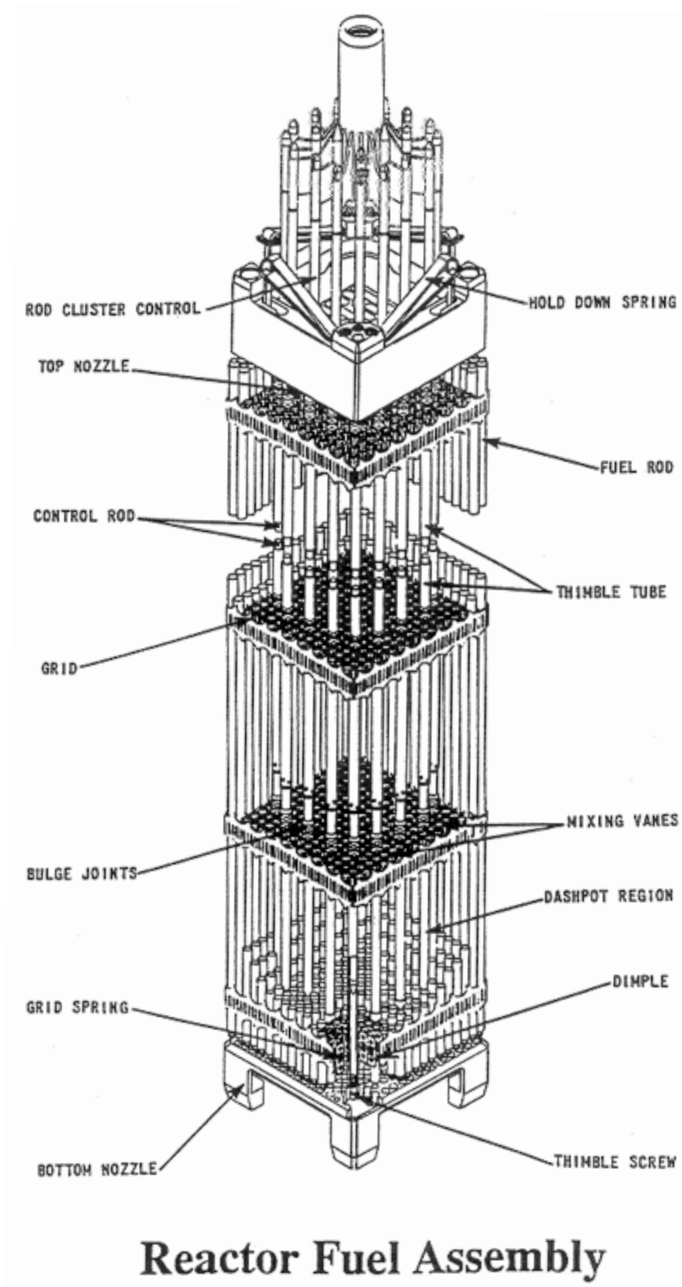

Figure 4-3: Typical PWR Fuel Bundle [NRC, 2013].

responsible for the entire nuclear power cycle. The two main structures in the reactor core are the fuel bundles themselves, and the support structure. The support structure consists of upper and lower support structures, and fuel core baffles, the purpose of which is to secure the fuel assemblies into the base of the pressure vessel [Ray, 2010]. The fuel assembles were treated as manufacture parts in the model rather than commercially available components for two reasons. First, the fuel assemblies are shorter than in conventional GW–scale reactors so a slightly different manufacturing process is necessary. Second, it was possible to calibrate the parametric model for the IRV by running the simulation for fuel assemblies out to commercial production quantities.

The fuel assemblies consist of 264 fuel rods, 25 control rod guide thimbles, grid assemblies, top and bottom nozzles, and a hold-down spring as in Figure 4-3 [NRC, 2013]. The number and length of the bundles is largely dependent on the proposed power output. However, the relationship between the number of bundles in a reactor core and the total power output is not quite linear. In the Westinghouse SMR, there are a total of 89, 8 foot long bundles with a power output of 225 MW [Westinghouse, 2011]. Whereas in the Generation mPower design, there are sixty-nine, eight foot long bundles with a power output of 180MW [Babcock & Wilcox, 2012]. For the generalized design, the power output used in the model was 100MWe. The number of bundles in the reactor core was 54 based on the critical heat flux and thermal output with efficiency estimated to be approximately 30%[Lamarsh, 1975]. The major components of the reactor core are the fuel rods, lower core support structure, core baffle, and upper core support structure. In order to be consistent with the larger output SMR designs, the effective length of the fuel rod was chosen to be 8 feet [NEI, 2012].

The nuclear fuel used in the PWR–based fuel rod assemblies was Uranium 235 in the form of a pressed oxide powder [IAEA, 1999a][Palheiros, 2009]. The cost of the fuel pellets was not contained in the SEER library, however, a price was determined to be approximately \$1152 per pound [WNA, 2011a]. The fuel pellets were housed in tubes made of Zircaloy [WNA, 2011]. This was a standard cladding material used in PWR reactor fuel assemblies. Zircaloy is a zirconium based metal alloy which was found to be priced near \$24.16 per pound [Ashby, 2010]. The remaining components: the upper and lower support structure, the fuel rod hold down bolt, control rod guide thimbles, and top nozzle were made of 18% Cr stainless steel priced at \$1.32 per pound [NRC, 2012].

Nuclear fuel pellets were initially treated as a purchased part using the price listed above. Each fuel rod was approximately 0.4 inches in diameter and 8 feet long, the fuel portion of each rod weighs 0.1 pounds, and with 54 assemblies of 264 rods, the weight of fuel per reactor core is approximately 1 ton. The zircaloy cladding is machined to form the tubular fuel pellet housing [WNA, 2011b]. Similarly, the fuel rod baffle, or the support grid is also machined from zircaloy. The SEER guidelines suggest that zircaloy processing is a highly complex process.

The upper and lower support structures are rolled, machined, and then heat treated [NRC, 2012]. Each of these processes is taken to be a highly complex process because of the emphasis on quality, and the need to meet very high standards of production. The fuel rod retention system consists of a spring and a bolt. The bolt is first cast, then machined and heat treated while the spring is rolled, machined, and heat treated [NRC, 2012]. These processes are highly complex according to the SEER guidelines.

Simulations of the LEAD plant suggest that labor would be the dominant cost driver of the reactor core (Figure 4–4) at 49±3% of the total reactor core cost. Materials were the next dominant driver at 31±2%

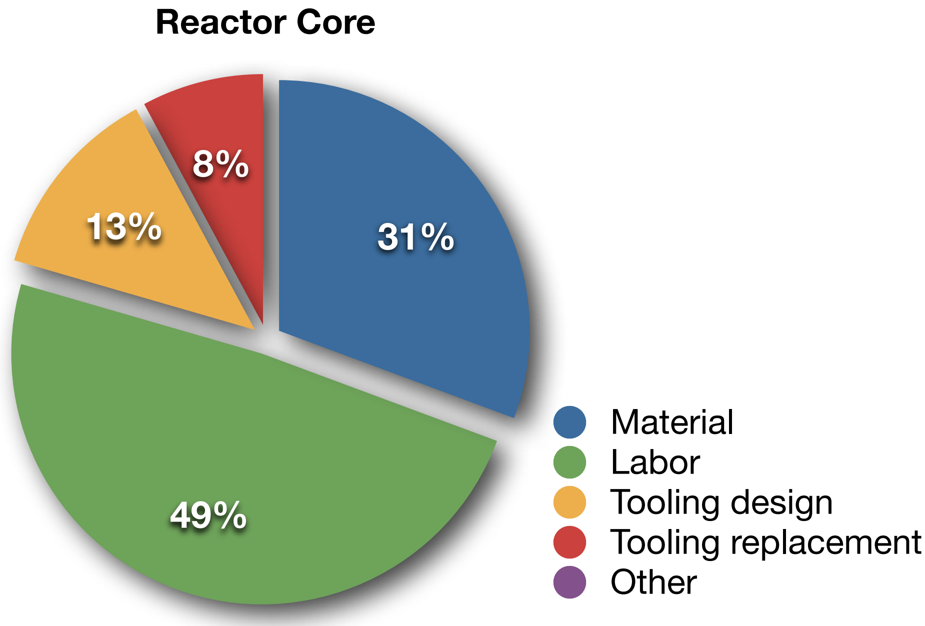

Figure 4-4: Production Cost Breakdown of Reactor Core by Cost Drivers

Cost Driver	% Cost of Component	Error as % of Total Component	Error as % of Total IRV
Material	31%	±2%	±1%
Labor	49%	±3%	±1%
Tooling Labor	13%	±1%	±0%
Tooling Replacement	8%	±0%	±0%
Other	0%	±0%	±0%
Total	100%	±6%	±2%

Table 4-4: Reactor Core: Cost Contribution and Error by Cost Center as % of Total Component Cost and IRV Cost

of the core cost. Table 4–4 details the costs and errors of the remaining drivers. The fuel assemblies due to the similarity to PWR fuel assemblies were used to both calibrate the model and set a means for predicting the effect of prior process knowledge on learning.

iii.) Steam Generator

The steam generator is the intermediate heat exchange manifold which mediates the exchange of heat between the primary and secondary coolants. Here, the primary coolant, which remains liquid, transfers its heat energy into the secondary coolant, through the surface defined by the steam generator tubes [US Atomic Energy Commission, 1974]. Through this exchange, the secondary coolant is converted into steam which is used to power a turbine generator. Based on the two larger SMR designs from Generation mPower and Westinghouse, there is a tendency towards a once-through, straight tube design for the steam generator [Westinghouse, 2011][Babcock &Wilcox, 2012]. The once-through, straight tube design consisted of a larger central tube which channels the primary coolant up and away from the reactor core. At the top of the central tube, the coolant was pumped into a number of smaller tubes that circulated the coolant back down into the reactor core [Gad, 2011][IAEA, 2011a]. The secondary coolant flowed over and around these tubes, where it was converted to steam in the process.

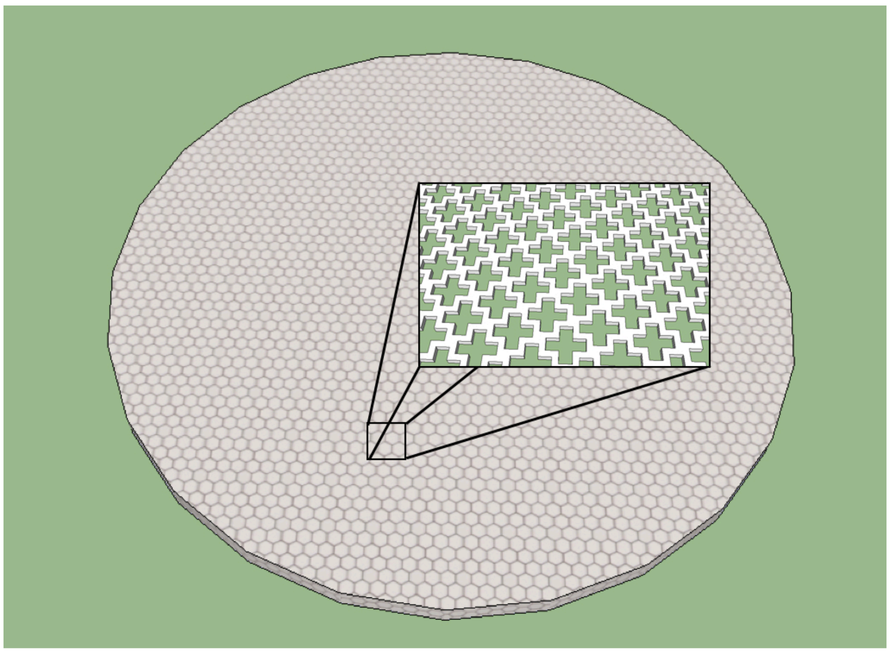

Figure 4-5: Typical Support PLate for Nuclear Steam Generator (quatrefoil design) [Shanghai, 2012]

The main components of the generalized steam generator used in our cost estimate were the tubes, support plate, tube baffles, inlet, and outlet [IAEA, 2011a]. The generalized design for the steam generator contained 9960 tubes with the dimensions 0.625” wide by 25’ long by 0.042” thick. The thickness and diameter of these tubes closely matched those used in the traditional, “u-tube”, design team generators [Green, 1995]. The length of the tubes was estimated from diagrams of the Generation mPower and Westinghouse SMR designs [Westinghouse, 2011][Babcock & Wilcox, 2012]. Additionally, the steam generators housed support plates, tube baffles, and coolant inlet and outlet nozzles [IAEA, 2011]. The support plates were large discs with pre-cut holes in them to retain the even spacing between the heat exchange tubes. Figure 4-5 illustrates commonly found designs used in support plates [Shanghai, 2012].

Because the heat transfer tubes, as well as the inlet and outlet nozzles, must endure the most extreme operating conditions, the material from which these parts were made was inconel 690 [NRC, 2012a]. Inconel 690 is a metal alloy which is the industry standard for steam generator parts as well as a

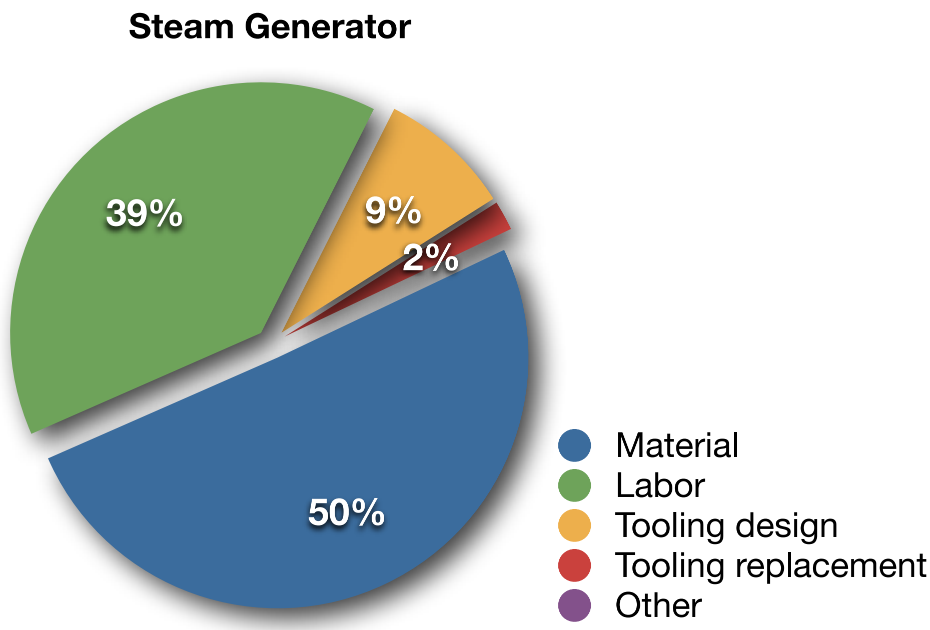

Figure 4-6: Production Cost Breakdown of the Steam Generator by Cost Drivers.

Cost Driver	% Cost of Component	Error as % of Total Component	Error as % of Total IRV
Material	50%	±2%	±0%
Labor	39%	±3%	±1%
Tooling Labor	9%	±1%	±0%
Tooling Replacement	2%	±0%	±0%
Other	0%	±0%	±0%
Total	100%	±6%	±1%

Table 4-5: Steam Generator: Cost Contribution and Error by Cost Center as % of Total Component Cost and IRV cost

number of other nuclear related applications due to its durability and corrosion resistance[Special Metals Corporation, 2012]. Inconel is a Nickel alloy which is priced at $16.48 per pound according to the SEER library. The remaining components are fabricated from a corrosion resistant 18% chromium stainless steel[IAEA, 2011a]. The stainless steel is priced at $1.32 per pound.

The steam generator production process was broken down by part. In the IRV steam generator, one of the defining components was the tubes used to transfer heat from the primary coolant to the secondary coolant. These tubes were the result of a fabrication process beginning with cast ingots of Nickel alloy

690, which were then pierced and rolled into rough tube shapes, before being machined and then heat treated [Nippon Steel & Sumimoto Metal, 2012]. The relative complexity of these operations was considered to be high. The inconel was continuously cast in bar form and cut into 41 pound ingots. These bars were then pierced and rolled into a rough tube shape. After the rough tube shape was achieved, the tubes were machined. Factories currently producing these tubes rely heavily on automation to ensure consistency in machining [Nippon Steel & Sumimoto Metal, 2012]. The modeling here utilized highly automated machining. This led to the components being small, and number of fabrication steps being small (primarily milling and facing), so the machining of the tubes was taken to be of intermediate complexity. The weight of the tubes during this process was reduced to 8 pounds with a total surface area of 800 in^2. After the forging was completed, the ring section was heat treated. Heat treatment was taken to be a marginally complex process.

The support plate maintained an even spacing in the tubes while maximizing tube contact with the secondary coolant without restricting coolant flow [R&N, 2012]. Plates of inconel were first machined to specifications, then a quatrefoil pattern (Figure 4-5) was laser cut into the plates before being heat treated. The machining was taken to be a moderately complex procedure, whereas the laser cutting was taken to be very highly complex. There were two support plates in the generalized steam generator. Each plate weighed approximately 6 tons with a surface area of 660 ft^2.

The tube baffles served as a housing for the mounting brackets for the tube-support plate assembly. The tube baffles were cast and machined from stainless steel [IAEA, 2011a]. The complexity of the casting and machining for the tube baffles was taken to be highly complex. The steam generator was assembled by automated TIG welding [Nippon Steel & Sumimoto Metal, 2012]. The final assembly including the welding was a very highly complex process according to the SEER guidelines.

Figure 4–6 indicates that the dominant cost driver in the steam generator was the materials cost which contributed 50±2% of the total. Table 4–5 shows that labor contributed 39±3% of the cost of the LEAD steam generator. The Monte Carlo modeling indicated an error of ±6% in the total cost of the steam generator. The steam generator itself using many components (tubes) that have been produced in quantity, however, the straight–through design is not common so there is a potential for learning here in assembly here.

iv.) Control Mechanism

The control mechanism regulated the reactor core thermal output. This was accomplished in the model by means of control rods which contained a neutron absorbing material. The control rods were moved up and down within the fuel assemblies, thereby limiting the rate at which neutrons were absorbed and emitted, and in turn limiting the release of thermal energy [Ishida, 2001. The depth of the rod penetration into the fuel assemblies determined the level of neutron exchange and was controlled by a motorized drive mechanism[Babcock & Wilcox, 2011]. Generally, each fuel assembly had a corresponding control rod assembly which was actuated by one control rod drive mechanism for each assembly[Stambaugh, 2010].

In the case of the generalized SMR design, the control rod drive mechanism was more complex than in a GW–scale PWR [Gunther, 1991]. Normally, in a PWR, the reactor core is situated at the bottom of a large pressure vessel with the control rods situated just above the fuel assemblies and the rods are actuated by an externally mounted drive mechanism. In an SMR IRV, the space above the reactor core is still occupied by the control mechanism, the difference being that the drive mechanism is no longer external to the pressure vessel [NEI, 2012]. The IRV configuration sandwiches the control mechanism between the reactor core at the bottom of the pressure vessel, and the steam generator in the upper middle section of the pressure vessel. This means that the control rod drive mechanism will be exposed to much of the heat and pressure enclosed by the pressure vessel [Finck, 2011].

The difference in configuration means that typical control rod drive mechanism designs were not applicable. Novel technology needed to be deployed in the generic design. Each of the SMR designs

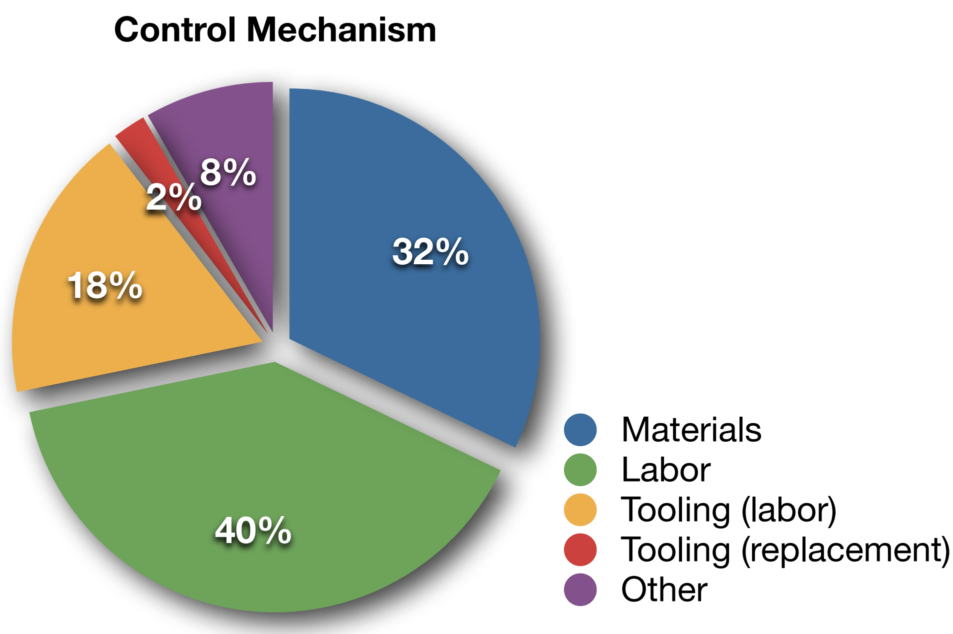

Figure 4-7: Production Cost Breakdown of the Control Mechanism by Cost Drivers.

Cost Driver	% Cost of Component	Error as % of Total Component	Error as % of Total IRV
Material	32%	±2%	±<1%
Labor	40%	±4%	±<1%
Tooling Labor	18%	±2%	±0%
Tooling Replacement	2%	±0%	±0%
Other	8%	±0%	±0%
Total	100%	±8%	±<1%

Table 4-6: Control Mechanism: Cost Contribution and Error by Cost Center as % of Total Component Cost and IRV cost

that the team examined had developed a proprietary solution to this problem, resulting in a general lack of available details on the subject. However, the critical nature of these components requires some approximation to be made to, even partially, capture the contribution of the control rod drive mechanism to the overall production cost estimates. Therefore, a common magnetic coupling drive mechanism was chosen as the design template for the generalized SMR control rod drive mechanism. The control rod drive mechanism consisted of an electric stepping motor, pinion gear, and magnetic coupling device [Babcock & Wilcox, 2011a]. The rods themselves were not different from those used in existing reactor control mechanisms. A central tie in rod supported a cruciform bladed structure around which the boron was formed. The base of the rod was outfitted with a speed limiter and handle that interfaced with the control rod drive mechanism [Tani, 1998]. The generalized control mechanism utilized eighteen bundles of twenty–four control rods. The twenty–four control rods per bundle corresponded to the twenty–four guide thimbles in the fuel rod assemblies. The number of control rod bundles in an SMR preserved the ratio of the number of control rod bundles to fuel rod bundles found in GW–scale PWR reactors.

In the control mechanism, there were two distinct systems: the control rods, and the drive mechanism. The control rod drive mechanism consists of an electric stepping motor, pinion gear, and a magnetic coupling device. The electric motor, pinion gear, and magnetic coupling device were treated as purchased parts for a total price of $1.6 million per IRV[Villaran, 1996][Hofmann, 2012][DMT 2012].

The control rods themselves were composed of a central tie in rod, a handle, a speed limiter, a neutron absorbent material, and a protective cladding. The central tie in rod, speed limiter, and handle are made from 18% Cr stainless steel. The neutron absorbent material used in many PWR control systems is boron because of the high absorption cross section. Boron was found to have a price per pound of $2300[LANL, 2012]. The cladding is made from the same zirconium alloy used in the reactor core which was priced at $24.16 per pound[Page, 1968][James, 2012].

The control rods consisted of a central tie in rod which was rolled and machined into a cruciform cross section. Welded to the base of the tie in rod, was a handle to which a speed limiter was affixed. A foil which holds the neutron absorbent material was machined to form around the tie in rod [Nakayama 2005]. The control rod blade consisted of a central zirconium alloy blade which was sheathed in boron. The zirconium alloy was machined from stock sheets. The machining of zirconium alloy was listed as a highly complicated process. This process continued in the fabrication stage where the component was laser cut using a CNC laser milling machine. This phase of production was much more complicated than the preceding machining. The blade was then heat treated. Heat treatment was taken to be a moderately complex process. Finally, boron was formed around the zirconium alloy blades. This process involved surfacing the boron in a moderately complicated machining process. The completed control rods were 8 feet long to match the fuel rod dimension, and the total control rod cluster weighed a total of 220 pounds.

The results of the Monte Carlo simulations (Figure 4–7) indicated that Materials and Labor were both strong cost drivers of the control mechanism of the IRV. Labor was responsible for 40±4% of the cost of the control mechanism and materials 32±2% of the cost (Table 4–6). The control rod drive mechanism is very unique to SMRs. The total error in the component cost was estimated to be ±8%. This is a subsystem where not much prior knowledge can be claimed.

v.) Coolant Pump

The mechanism by which the primary coolant is circulated in a PWR NSSS is the coolant pump. In a full-scale nuclear reactor, the large reactor core supplies a tremendous amount of thermal energy which must be transferred to the secondary coolant through the multiple steam generators [NRC, 2012]. The number of coolant pumps used in a GW–reactor is variable and depends largely on the design of the pump and the optimal flow rate for the reactor design. Not all SMR designs have coolant pumps. The NuScale design uses natural convection currents to cycle the primary coolant inside their IRV and

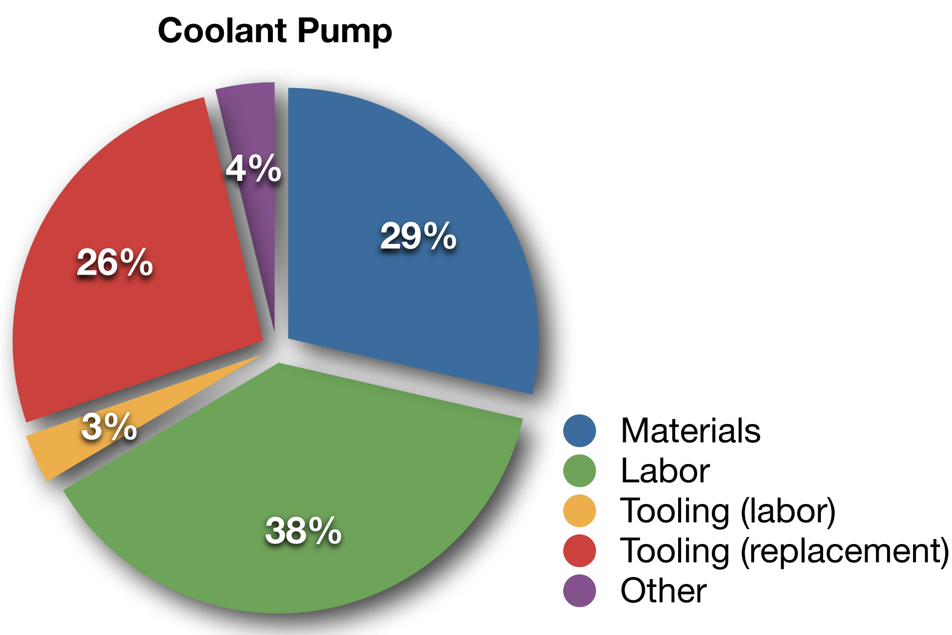

Figure 4-8: Production Cost Breakdown of the Coolant Pump by Cost Drivers.

Cost Driver	% Cost of Component	Error as % of Total Component	Error as % of Total IRV
Material	29%	±8%	±<1%
Labor	38%	±5%	±<1%
Tooling Labor	3%	±<1%	±0%
Tooling Replacement	26%	±0%	±0%
Other	4%	±0%	±0%
Total	100%	±13%	±<1%

Table 4-7: Coolant Pump: Cost Contribution and Error by Cost Center as % of Total Component Cost and IRV Cost

therefore does not require a coolant pump[Welter, 2010]. However, the designs put forth by Westinghouse and Generation mPower each implement eight and ten coolant pumps, respectively [Westinghouse, 2011][Babcock & Wilcox, 2012]. The generalized design has a moderate power rating so eight coolant pumps were used to cycle the primary coolant in the generalized IRV. The basis for the design of the coolant pump was the same as those used in the AP1000 reactor plants. It consists of a flywheel, impeller, diffuser, nozzle, and motor inside of stainless steel casing [Carr, 2006][Mitsubishi, 2012].

The main components of the coolant pump were the flywheel, the impeller, the diffuser, the nozzle, and the casing. These components were fabricated from 18% Cr stainless steel[NRC, retrieved 2012]. The motor was a commonly available purchased part. The price for the motor was determined from the price of industrial motors used for similar applications ($100,000)[Claverton Energy, 2012].

The coolant pump casing was much like the IRV pressure vessel, both in form and function. As a result, the process by which it was produced was nearly identical. After casting and forging, the separate case components were heat treated and machined to specification. Welding the components together formed the final shape of the pump casing [Kitch, 2012]. The casting and forging were taken to be highly complex to very highly complex operations. The heat treatment for the case components was moderately complex. Machining and welding the separate case components was a very highly complex process. The final coolant pump case weighed 15,000 pounds with a surface area of 3200 in^2.

The impeller, diffuser, and nozzle were fabricated using a similar production process. Beginning with casting and forging, these parts were machined and heat treated[Wepfer, 2012]. The profile of the complexity of each of these operations mirrors those of the pump casing. The impeller weighed 70 pounds and had a surface area of 370 in^2. The diffuser weighed 200 pounds and had a surface area of 1300 in^2.

The flywheel begins with casting which was taken to be highly complex process. Because the flywheel spins at high rpm, it must be balanced to minimize the vibrations which made the machining of this component very highly complex [Carr, 2006]. After machining, the flywheel was heat treated in a moderately complex process. The final flywheel weighed 3000 pounds and had a surface area of 2600 in^2.

Figure 4–8 shows the simulation results for the coolant pump. This was one of the more interesting components as three of the cost drivers play a significant role in determining the final component cost. Labor (Table 4–7) was the largest cost driver at 38±5% of the cost. Materials contributed 29±8% to the total pump cost. Tooling replacement was also significant at 26±0% of the coolant pump cost. The error of coolant pump cost was calculated to be ±13%.

vi.) Pressurizer

In a typical PWR reactor, the primary coolant loop employs liquid water as a coolant to transfer heat from the reactor core to the steam generators. However, at 600 °F, water is well above the boiling point and at standard pressure would be in the gaseous state. To suppress the phase change from liquid to gas, the reactor pressure vessel maintains an internal pressure of approximately 14 MPa [NEI, 2012]. To maintain this internal pressure, the nuclear steam supply system employs a pressurizer. To optimize the function of the model IRV and to ensure safe operating conditions, a pressurizer was used to regulate coolant pressure by means of a relief valve and a heater [Cheng, 2009]. When the pressure was too low, the heater increased the coolant temperature, when the pressure was too high, the relief valve allowed the pressure to dissipate to an optimum level. In a typical PWR, the pressurizer is contained in its own vessel and is situated between the steam generators and the reactor vessel [Takasuo, 2006]. In many SMR designs, the pressurizer is integrated into the top of the IRV, above the steam generator [IAEA,

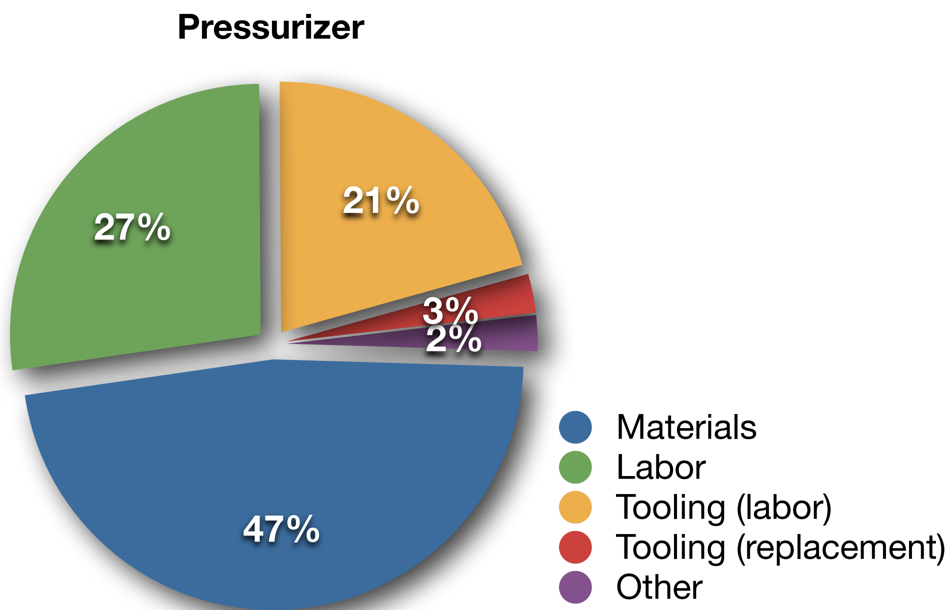

Figure 4-9: Production Cost Breakdown of the Pressurizer by Cost Drivers.

Cost Driver	% Cost of Component	Error as % of Total Component	Error as % of Total IRV
Material	47%	±2%	±0%
Labor	27%	±<1%	±0%
Tooling Labor	21%	±<1%	±0%
Tooling Replacement	3%	±0%	±0%
Other	2%	±0%	±0%
Total	100%	±2%	±<1%

Table 4-8: Pressurizer: Cost Contribution and Error by Cost Center as % of Total Component Cost and IRV Cost

2011]. In the design of the generalized IRV, the pressurizer retained its own vessel, however, it was partially integrated into the IRV exterior.

The pressurizer was made up of the following components: a heater, a safety and relief valve, a spray nozzle, and a pressure vessel [Westinghouse, 2006]. The pressure vessel was made from the same SA-508 steel used in the reactor pressure vessel. The relief valve and the spray nozzle were made from 18% Cr stainless steel [NRC, 2012]. Finally, the heater used in the pressurizer was a 30 KW water heater, and was treated as a purchased off-the-shelf part at a cost of $10,000[Thermocoax, retrieved 2012][Omega, retrieved 2012].

The pressure vessel for the pressurizer was constructed using the same procedure and complexity profile as the reactor pressure vessel. The pressurizer vessel was cast in sections before forging, machining, and heat treatment. The separate segments were then welded together to form the complete enclosure. The pressure vessel weighed 850 pounds and had a surface area of 1500 in^2.

The results of the Monte Carlo simulation of the pressurizer are shown in Figure 4–9. Materials costs dominate the LEAD pressurizer, contributing 47±2% of the total cost. Table 4–8 shows that labor is also significant with labor at 27±<1% and tooling labor at 21±<1% of the cost of the pressurizer. One of the most important results was the the pressurizer does not contribute significantly to the total cost of the IRV.

D. Results of Simulation on LEAD IRV

The parametric modeling of the integrated reactor vessel of the LEAD SMR has produced interesting results. The cost estimates for the LEAD IRV can be detailed to highlight different costs such as reactor subcomponent or manufacturing variable. Figure 4–10 and Table 4–9 details the production costs in terms of cost driver such as materials, labor, tooling (replacement), tooling (labor), and other. All cost drivers are presented as a fraction of the total IRV cost. It was clear that labor and materials dominate the manufacturing costs of the IRV, combining for 90% of the total costs of the LEAD IRV. Any costs savings that may be obtained in these two areas will significantly reduce the cost of the IRV.

Figure 4–11 and Table 4–9 show the cost breakdown of the IRV in terms of the Pressure Vessel, Reactor Core, Steam Generator, Control Mechanism, Coolant Pumps, and Pressurizer. The data shows that the two dominant contributors to the cost of the LEAD plant are Pressure Vessel at 39±3% of the total cost with the initial cost of the fuel assemblies including the initial fuel load at 32±2%. Given the large number of fuel assemblies that have been produced and the minor modifications needed to reduce the size of the fuel assemblies from GW–scale size to the SMR–size it was expected that large cost reductions could be obtained in the reactor core by applying a credit of prior process knowledge in fuel assembly production. This will be discussed in detail in the following section.

It was also clear from the simulation that the Pressurizer is not a major concert for the cost of the IRV with a contribution of less than 1% of the overall cost. The Control Mechanism contributes approximately 5±<1% to the cost of the factory built LEAD IRV. Given the lack of prior knowledge of utilizing control rod drive mechanism internal to the IRV, this was a good result. Little credit for prior knowledge does not hurt the cost of the IRV due to the small contribution of the control mechanism.

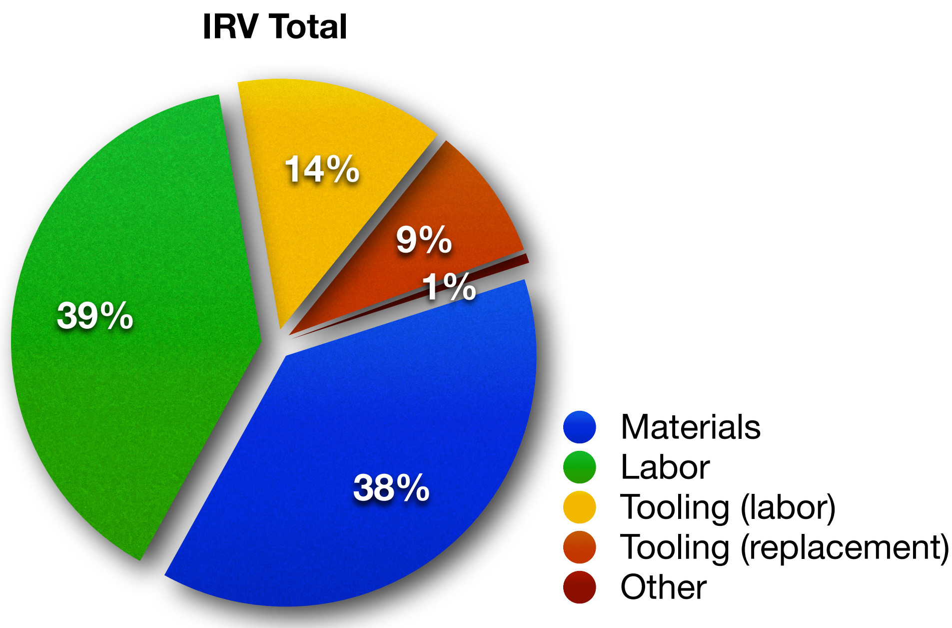

Figure 4-10: Production Cost Breakdown of the IRV by Cost Drivers.

Cost Driver	% Cost of Component	Error as % of Total IRV
Material	38%	±2%
Labor	39%	±3%
Tooling Labor	14%	±1%
Tooling Replacement	9%	±0%
Other	<1%	±0%
Total	100%	±6%

Table 4-9: IRV Total: Cost Contribution and Error by Cost Center as % of Total Component Cost

This modeling allows for the exploration of phase (parameter) space within the limitations of the model reactor that was designed. For this initial exploration of the factory manufactured IRV of a model SMR, the chief economic quantities of interest were the learning rates and the manufacturing lot size. Both of these quantities depend far more heavily on the proportional contributions of the main cost drivers (materials costs, labor, tooling replacement, tooling labor/design, and other) than the absolute values of the cost, as will be discussed later. The final breakdown of the IRV cost drivers is derived from a combination of the individual components, and is presented below in two ways.

The estimates produced above form the basis for the parametric modeling of the manufacture of a generalized LEAD SMR IRV. In this case, LEAD loosely means the IRV proof of principle, where each component (with few exceptions) was custom built in the absence of the knowledge that many of the components have been in commercial production for decades. This is, of course, completely unrealistic. Any SMR vendor factory will attempt to make full use of the learning that has taken place, and will apply this pre–existing knowledge towards IRV production. It is understood that no SMR vendor will build a LEAD plant, like the one described by the data above, due to the existence of this prior knowledge. The next step in the exploration of the parameter space of the model was to replicate the

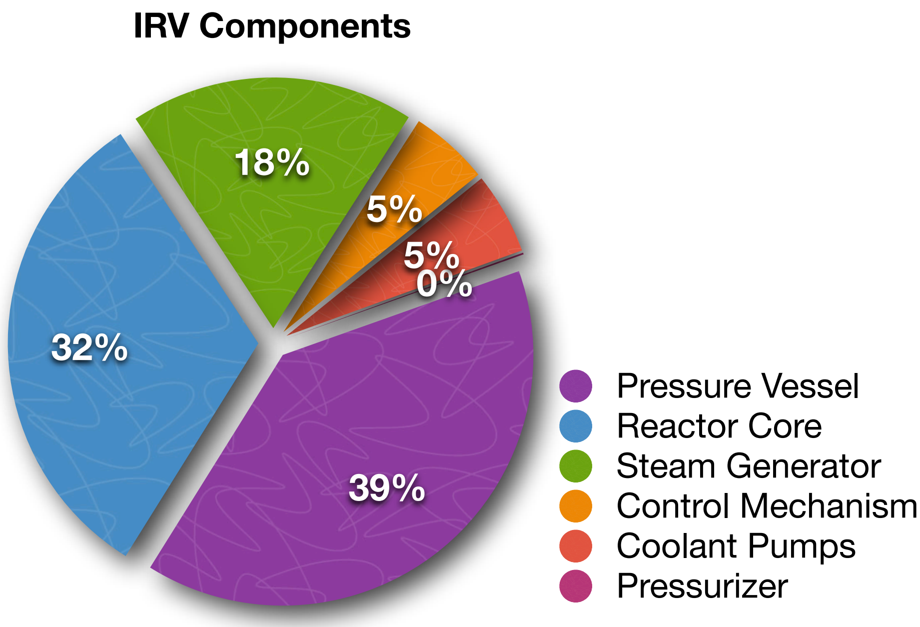

Figure 4-11: Production Cost Breakdown of IRV by Physical Components and Subsystem

Cost Driver	% Cost of Component	Error as % of Total IRV
Pressure Vessel	39%	±3%
Reactor Core	32%	±2%
Steam Generator	18%	±1%
Control Mechanism	5%	±<1%
Coolant Pumps	5%	±<1%
Pressurizer	<1%	±0%
Total	100%	±6%

Table 4-10: IRV Total: Cost Contribution and Error by Component and Subsystem as % of Total Cost.

effect that prior knowledge would have on the production cost and learning rates of SMR production. Having fully developed a usable parametric model for the generalized IRV, as well as the LEAD cost estimates, it is possible to begin the modeling of the SMR learning rates, a necessary first step to understanding the effect of crediting prior production knowledge.

V. Learning in SMR Manufacture

A. Introduction

The economic viability of SMRs will depend upon how the production cost changes as a function of unit production number. The most common method for modeling the evolution of the production cost utilizes learning curves[Rosner, 2011][Paul, 1991]. Under most circumstances, manufacturing costs diminish over the lifetime of a given production model[Louis, 1979][McCabe, 1996]. One of the more prominent instantiations of this principle is "Moore's Law" from the semiconductor industry[Moore, 1965]. Moore's Law is often stated in terms of the doubling of the number of components in an integrated circuit device. However, Moore described this doubling as being due to the reduction of the cost of each component on an integrated circuit chip, i.e. the learning curve of production.

The phenomenon of learning curves was first properly identified and explained by Theodore Paul Wright in 1936 through his work based upon the nascent aircraft industry [Wright, 1936]. Originally, the reduction in cost was seen as a consequence of learning on the part of those responsible for construction and assembly [Gregory, 2006]. However, it has since been recognized that decisions made by management, technological improvements, and other efficiency gains lead to reduction in production costs as well [Gregory, 2006][Lowenthal, 1987]. The use of learning curves is extensive in the field of cost estimation [Stump, 2012] and it is clear that learning curves can provide valuable insight into the viability of a prospective SMR industry.

i.) Modeling Learning

There are two predominant descriptions of learning curves: the Wright Model [Wright, 1936] and the Crawford Model [Lee, 1997]. Both the Wright and Crawford Models utilized learning curves based upon a log–linear power function. The main difference between the models is that the Wright Model determines a cumulative average cost of producing x units while the Crawford Model uses the marginal cost of production. Both models are discussed in detail in Appendix B.

$$TC(X)=TC\cdot X^b \qquad \text{Eq. 5-1}$$

The following analysis is based on the learning theory proposed by the Wright model[Wright, 1936]. The basic form of the Wright model is given by Eq. 5-1. The total cost of producing the X^{th} unit, $TC(X)$, is obtained by multiplying the total cost of the first unit (TC) by the unit number, X, raised to the b power, where b is the quantity known as the learning slope. The learning slope is so named because when Eq. 5-1 is plotted on a log–log graph, the curve is linearized with the slope of the new line equal to b. The so-called learning slope is the only free parameter in Eq. 5-1. The slope, b, contains all of the information pertaining to the evolution of production costs [Gregory, 2006]. The learning slope can ultimately be expressed as the ratio of two logarithms of which the argument of the numerator is known as the learning rate. It is this number which singularly captures and quantifies the learning that takes place in a given model. A full description of the derivation of the learning rate from the learning slope can be found in appendix A. The learning rates for the total IRV and IRV components must be determined in order to further develop the model of the factory manufactured IRV and the economics thereof.

ii.) Estimating the Learning Rate

The task of modeling the learning curves for the manufacture of the IRV and IRV components is a difficult task. Clearly, if one has actual production data, the learning rate may be determined by fitting a curve to the data set. Using the result of the curve fitting, the learning slope can be determined [Bailey, 1997]. However, SMRs have not been produced so the necessary data does not exist. The purpose of this effort is to model the likely production cost data needed to determine the total learning expected to be observed in the manufacturing process. The data is developed by creating a model that captures the majority of the components of the IRV of an SMR as described previously. Next, the learning rate must be built from the bottom up using reasonable values based upon learning rates for the individual work elements and production processes that used to build the generalized SMR design [Koomey, 2007] [Neiji, 2008][Oswald, 1991]. This was done by supplying SEER-MFG with estimates of learning rates for each of the production processes involved in IRV fabrication [SEER, 2011].

When talking specifically about reduction in production cost resulting from learning, operations performed by humans have the greatest potential for learning[Goldberg, 2003]. Such processes have an associated learning rate of 70% (progress rate 30%)[Goldberg, 2003]. Whereas fully automated processes undergo no learning, due to the unintelligent nature of assembly line robots, these can still experience efficiency gains from advancements in technology and new programming [Lightbourne, 2009]. Therefore, the learning rate for automated processes is much lower, between 90%-95% (progress rate 5%-10%). Most production processes consist of a combination of automation and skilled labor. A proven methodology [Rodney, 1995] for estimating the learning rate of a manufacturing process involves the determination of the relative fraction of automation and skilled labor, and then averaging the associated learning rates (Table 5-1). Only by fully detailing the manufacturing process was it possible to determine the balance between time spent in manual fabrication and time spent in automated fabrication.

In order to predict the learning curves for the IRV, it was necessary to determine the proper range of learning rates to use for the different processes involved in the production of the SMR components. SEER–MFG has a database with learning rates for known manufacturing processes. These were

Ratio of Skilled Labor to Automation in Production	Learning Rate	Progress Rate
75/25	80%	20%
50/50	85%	15%
25/75	90%	10%

Table 5-1: Estimating Learning Rate for a Given Production Using a Ratio of Skilled Labor ti Automation [Rodney, 1995].

utilized whenever possible. For other aspects of production, the learning rates were determined by looking at the appropriate literature[Rodney, 1995]. However, many components of SMR production used novel technologies. In these situations, it was possible to derive an initial learning rate by estimation based upon similar processes in allied industries. In order to make the best analogies between SMR production and an allied industry, the following criteria were utilized. First, the SMR component should be similar in composition. Second, the production processes should be similarly structured. Finally, there should be some similarity in the purpose or function [Wilson, 1998]. It was possible to refine this estimate further by specifying the nature of the production process. Once a thorough analysis of a component was completed and the details of the materials and production were identified, they were assigned a known learning rate. Table 5-2 contains many of the learning rates used throughout the parametric modeling of IRV manufacture. Monte Carlo modeling based upon the starting production weighted learning rates was used to generate a more accurate estimate of the learning rate for each component of the IRV.

Industry/Operation	**Learning Rate**
Aerospace	85%
Shipbuilding	80-85%
Electronics Manufacturing	90-95%
Complex Machine Tools	75-80%
Machining	90-95%
Electrical Operations	75-80%
Welding	90%
Purchased Parts	93-96%
Raw Materials	85-88%

Table 5-2: Learning Rates for a Number of Industries, Manufacturing Processes, and Components [Rodney, 1995].

iii.) Learning Rates by Cost Driver

Because learning is manifested as a reduction in the total production cost of manufacturing, it is useful to look at the learning due to the individual cost drivers [Ryan, 2012][Ashish, 2007]. It was clear from the application of the learning rate estimates to the SEER–MFG model that the main reductions in cost will be realized in both labor and manufacturing. However, it is not necessarily true that the learning confined to these factors. For this reason, it is useful to mention how learning is borne out in each of the cost drivers.

a.) Labor

The learning rates in the total labor are component specific and are determined by the balance of fabrication and assembly processes used to produce the IRV components of the SMR. Labor charges were determined largely by the production processes implemented in IRV manufacture. The production processes central to the labor cost were machining, welding, casting, forging, heat treatment, setup, and assembly [NRC, retrieved 2012]. Their associated learning rates are 90-95%, 90%, 90%, 98%, 97%, 90%, and 90% respectively [Rodney, 1995] [SEER, 2012]. The overall labor learning rate was determined from the parametric modeling of the overall production of the IRV utilizing SEER-MFG.

b.) Materials

As stated earlier, the natural volatility of the markets make predicting the price of materials an difficult task. Therefore, as a necessary simplification, the price of materials used in the construction was taken to be fixed. Despite this, the cost of materials does tend to diminish over the course of production. This phenomenon is associated with efficiency gains and when possible when purchased in bulk quantities. The factory workers make fewer mistakes, the machines become less wasteful, etc. as experience is gained. The learning rate in the cost of materials was taken to be between 93-96% [Rodney, 1995] which was consistent with the learning rate for purchased parts as well given in Table 5-2.

c.) Tooling Labor

The tooling labor cost is the portion of the tooling cost which is related to the labor necessary to augment, setup, or retool the factory and the production machinery contained therein [Maldonado, 2012]. Because these processes are mostly manual labor and generally are not automated, a learning rate of 80% was estimated using the method detailed above [Rodney, 1995].

d.) Tooling Replacement and Other Costs

Tooling replacement consisted of the cost of replacing the consumables during manufacturing. As such, and as with all purchased parts/off-the-shelf parts, these are taken to be products which are fully mature and do not undergo any appreciable reductions in cost to the vendor. Therefore, the learning rate assigned to these is 100%.

B. LEAD Learning Rates

The term “LEAD” is a term which appears frequently when discussing industrial manufacturing. Commonly, LEAD refers to the first complete, functional version of some product. Here, the LEAD IRV is modeled as built in a dedicated factory setting. However, it was modeled under the assumption that no prior knowledge that could be used to improve manufacturing existed. There are good reasons that suggest this assumption regarding prior learning is incorrect. This starting assumption does allow for the most flexibility in the model. The model could be adjusted for pre- existing knowledge from this starting point. Future effort should also focus on lowering the initial cost by maximizing the smartness of design which was not a focus of the model development work described here. The best design will likely allow for targeted investment in innovative equipment and tooling for a factory which will affect the prediction of the learning curves; it will shift down the start of the learning curve, similar to prior experience. As only a single design was investigated in this study, the no prior learning scenario was used to establish a limiting case on the learning in IRV production.

The learning rate for the LEAD IRV was simulated using the values for the learning rates of each of the constituent fabrication processes and the range of applied learning rates for each cost driver. Each simulation consisted of a Monte Carlo process where parameters were varied at random within their specified range which resulted in a single unit cost[Rubinstein, 2007]. The Monte Carlo simulation was repeated one thousand times for each unit do determine a confidence level of the measurement. This procedure was carried out for multiple unit numbers to determine the change in total production cost that is expected to be observed in the IRV manufacturing. The results of the simulation for a lot size of a single IRV are presented in Figure 5-1. The production cost of all IRVs were normalized to the cost of the first unit. The solid line indicates a learning rate of 93% for the LEAD IRV produced with no pre-existing manufacturing knowledge credited. The dotted lines in blue indicate the margin of error in the simulation using a confidence level of 85%. To reiterate, this error presented within Figure 5–1 is the error due to the modeling process and can not capture the errors inherent to the model itself. Simulation error does not include error in the initial cost estimation. The error in the learning curves come from the random variation within the Monte Carlo simulations of the the costs, using a normal distribution around a calculated mean value. The total error in the model could be reduced by using detailed machine drawings, exact number of welds, placement of bolt holes, and any other detailed processes knowledge of manufacturing. As described above, SEER-MFG attempts to capture this in amount of materials used but the model can be improved by inputing more detailed information on each IRV component as it becomes available. This lack of complete information while setting up the model was the reason that no total cost of manufacturing is given in this work.

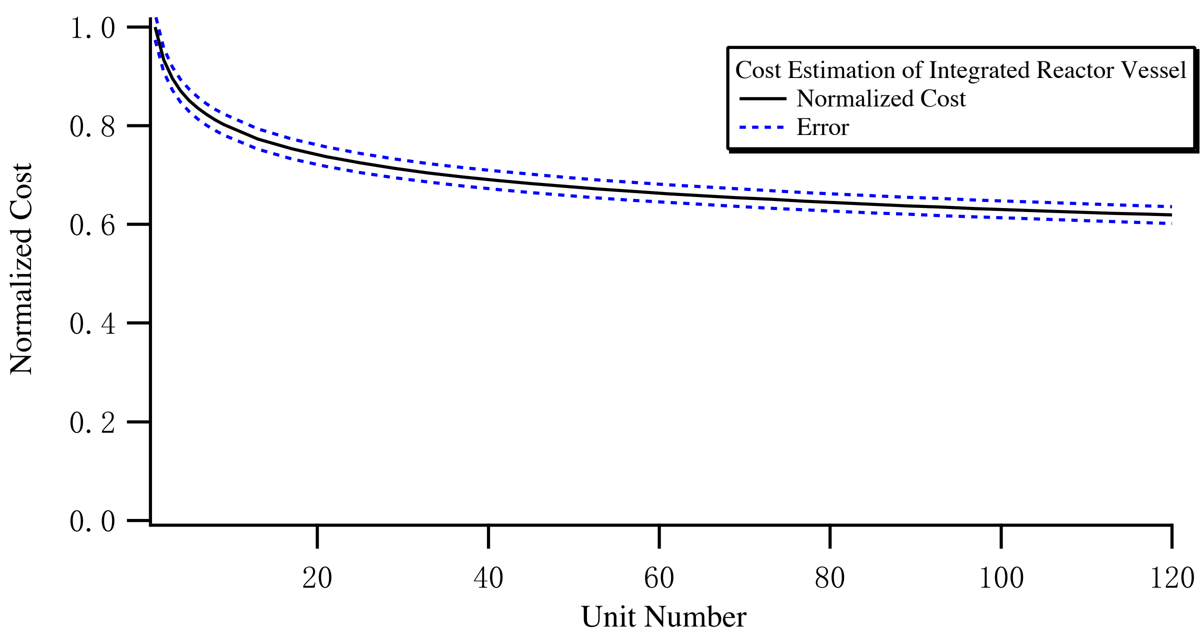

Figure 5-1: Learning Curve for the LEAD IRV in Lot Sizes of 1

C. Developing Methods For Crediting Prior Learning

In developing the learning curves for the LEAD IRV, a clear example of how to credit prior learning became evident. LWR reactors have been in use for many years in the U.S. [WNA, 2012a]. As a result, certain key components have become the basis for commercial industries. As one example, one can examine the fuel assemblies in the reactor core. The fuel assemblies are fairly standard parts [NEI, 2004] that have been manufactured for years. They have been commoditized. Therefore, the absolute cost of fuel assemblies, like those implemented in the generalized IRV design, is a known quantity [WNA, 2011a]. By starting with a case of no assumed prior learning and running the simulations of the learning curve out to the number of fuel assemblies that have been produced, it was possible to compare the prediction of the model to the real cost of a fuel assembly. Figure 5–2 shows the results of the simulation of the fuel assemblies.

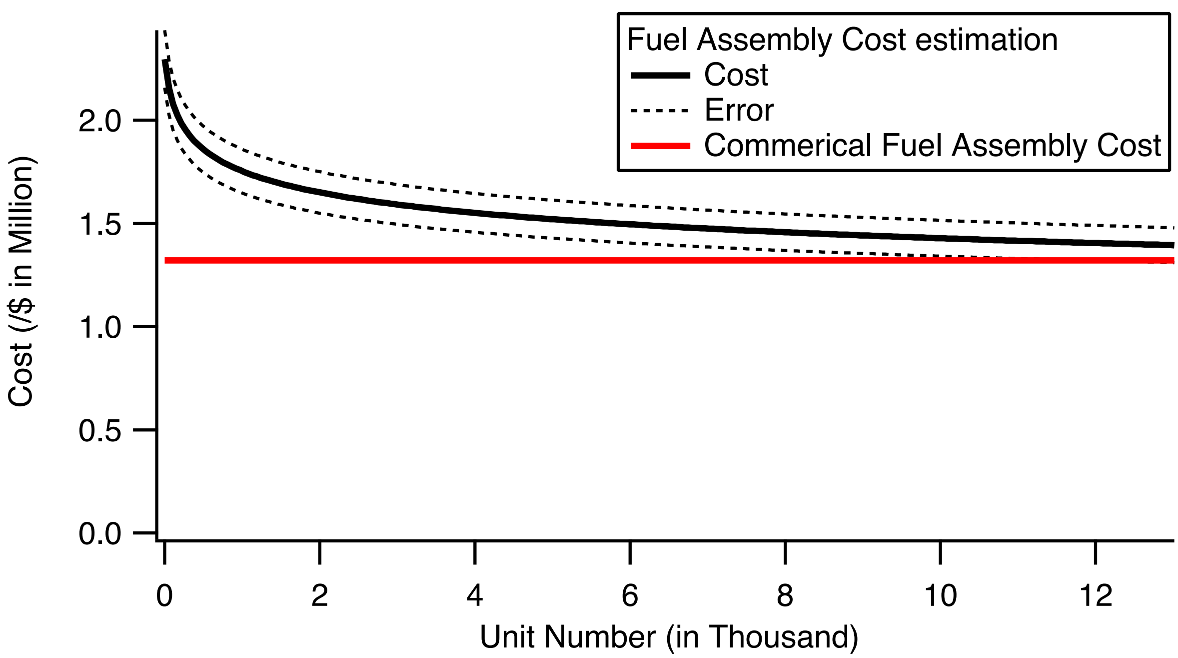

Figure 5-2: Learning Curve for the LEAD Fuel Assembly

Records indicate that the AP1000 reactor fuel assemblies, a design similar to that which is used in the generalized IRV, has been in production since 1997 with more that 12,700 units produced by Westinghouse[Ray, 2010]. Using 12,700 as the number of units to simulate, the LEAD curve produced a production cost estimate of $1.49 million, which is very near to the listed price of $1.3 million [WNA, 2011a]. It is reasonable to compare the production cost of the fuel assembly to a commercial price for a fuel assembly because the market for fuel rods is a well established and competitive. This competitive environment limits the potential profit levels. Another source of discrepancy is that they model did not have access to detailed fuel assembly drawings. It is expected that the predicted cost differential could be reduced if the model could be updated with detailed assembly drawing of the fuel assemblies.

In fact, it was comforting that the model predicts a slightly higher production cost of the fuel assemblies. The nuclear community has seen far too many unreasonably low cost estimates that ultimately were revised upward [Grubler, 2010][Schlissel, 2008]. The team wanted to avoid this scenario. If the absolute cost estimates for the IRV components of the SMR are proven out to be slightly higher than in reality, the model will have performed a reasonable job of providing bounds on the costs of SMR production which will be very useful for making future policy decisions. This is the ultimate reason that SEER–MFG was developed; to place bounds of the production cost of a device that can be used to determine if the production of a device was worth pursuing[SEER, 2012].

This process of using the number of units previously produced introduces the concept of prior learning. This technique was used to refine the cost estimating of IRV production. The FOAK estimates were determined by realizing the idea of prior learning, and incorporating this effect into the simulations of the production cost estimates.

D. Credit For Prior Learning

The purpose of developing a learning curve model for the manufacture of the IRV of an SMR was to understand the evolution of the production cost as more units are produced. At this point, the foundation of the learning model has been established as well as the parameters needed to obtain the learning rates for the total cost of the IRV in terms of the cost drivers and the individual components that make up the IRV. To this point, the simulations have involved a LEAD IRV. This value is not, strictly speaking, a valid value for *TC* in equation 5-1. This is because the LEAD plant was simulated as being constructed entirely from scratch without the benefit of any prior experience to aid in manufacture. A better representation of learning in the SMR manufacturing industry needs to incorporate the fact that much of the manufacturing technology has been in use in the nuclear industry for decades. The learning model needs the value of *TC* to better reflect the actual cost of the first production unit. To transition from the LEAD to the first production unit, or FOAK, the learning model will be employed to fashion the concept of crediting knowledge [Rosner, 2011].

Crediting knowledge is a very simple concept if the learning model is already understood. Crediting knowledge is the idea that unless a technology is, from the ground up, completely novel, then that technology stands on the shoulders of the industries that precede it [Read, 2000]. Stated in terms of the model developed thus far, each of the IRV components stands to benefit from knowledge credited to existing industries. Pre-existing knowledge was incorporated into the SEER-MFG model by inputing the number of similar components (like fuel assemblies) previously produced.

Therefore, the FOAK cost estimates were formed from the composite effect of the learning derived from the initial LEAD IRV model. This is the advantage of this particular model. By building an open starting point of the LEAD model, different amounts of prior learning can be credited for each component within the IRV. This does lead to a tremendous amount of phase space that can be explored to both predict areas that can be improved and where learning can be most realized. However, it was also possible to over credit existing knowledge. It was important to consider what amount of learning can reasonably be transferred from prior experience in existing industries.

i.) FOAK Cost Estimates with Knowledge Credited

The LEAD production cost estimates in Chapter 4 suggest that the cost of the IRV was largely determined by the cost of the pressure vessel, reactor core, and steam generator. Learning that could be transferred from existing industries in these areas would reduce the production cost of the FOAK IRV. Crediting knowledge in these components must reflect the likely levels of prior learning expected to be experienced.

In the case of the fuel assemblies, the results from the simulation of the learning curve and the associated cost reduction, strongly indicated that prior knowledge would have a large effect on the production cost of the reactor core [Izumi, 2000][NEI, 2004]. This was due to the large contribution of the fuel assemblies to the cost of the reactor core[WNA, 2011a]. This prior learning was incorporated into the simulations of the IRV of the FOAK SMR.

Similarly, the steam generator will also benefit from prior learning. Here the transfer of learning is specifically applied only to the steam generator tubes. Steam generators used in PWR reactors have been a commercial product for decades. At least, 297 steam generators have been produced by Babcock & Wilcox [Babcock & Wilcox, 2012b]. With over 10,000 steam tubes in each steam generator [NRC, 2012a], it would be unrealistic to neglect the learning that will be transferred to SMR manufacturing from the tubes. The generators themselves are being used in new ways, incorporated with the IRV of the SMR. Learning was not applied to the full steam generators.

Finally, the prior learning in the manufacture of pressure vessels must be considered. Here, the application of crediting knowledge is complicated by a few factors. The first was that despite the emphasis on replicating the production process used in manufacturing the AP1000 reactor vessel [JSW, retrieved 2012a], the IRV pressure vessel was not identical. Also, the number of pressure vessels manufactured did not approach the number of steam generator tubes or fuel assemblies produced. Therefore, the pressure vessel was taken to be a novel component in this estimate of the FOAK costs [Jaber, 2008][Petrakis, 1997].

Another component that needed to be considered was the control mechanism. One could argue that because the fuel assemblies were modeled with high levels of prior learning, the control rods should be treated similarly [Gunther, 1991][Grove, 1990] because fuel assemblies are always paired with control rods and their drive mechanisms. Unfortunately, this is not the case for the control rod drive mechanism in the SMRs. As discussed previously, in an SMR IRV, as opposed to a traditional LWR, the drive mechanism is internal to the pressure vessel and therefore is subject to the extremes of temperature and pressure typical of nuclear power generation[Westinghouse, 2011][Ishida, 2001]. Even though the control mechanism includes the control rods which may be very similar to the traditional design used in existing PWRs, the specifics of how they integrate with the new drive mechanism are unknown. In recognition of the uncertain nature of the design elements, no learning was credited to the production of the control mechanism.

The modeling of the FOAK IRV resulted in the cost drivers that are presented in Figure 5–3 and Table 5–3 in terms of the production costs such as materials, labor, tooling (replacement), tooling (labor), and other. All cost drivers are presented as a fraction of the total FOAK IRV cost. As in the case of the LEAD IRV (Table 4–8), labor and materials dominate the manufacturing costs of the IRV. The total cost of these components though has been reduced to 78% of the cost of the LEAD IRV. While it appears as if the labor has become more costly (44% vs 39%), and the materials have become significantly less costly (33% vs 38%), in actuality the absolute cost of both was reduced due to the reduction in the cost of the FOAK unit which costs 22% less than the LEAD unit. These apparent

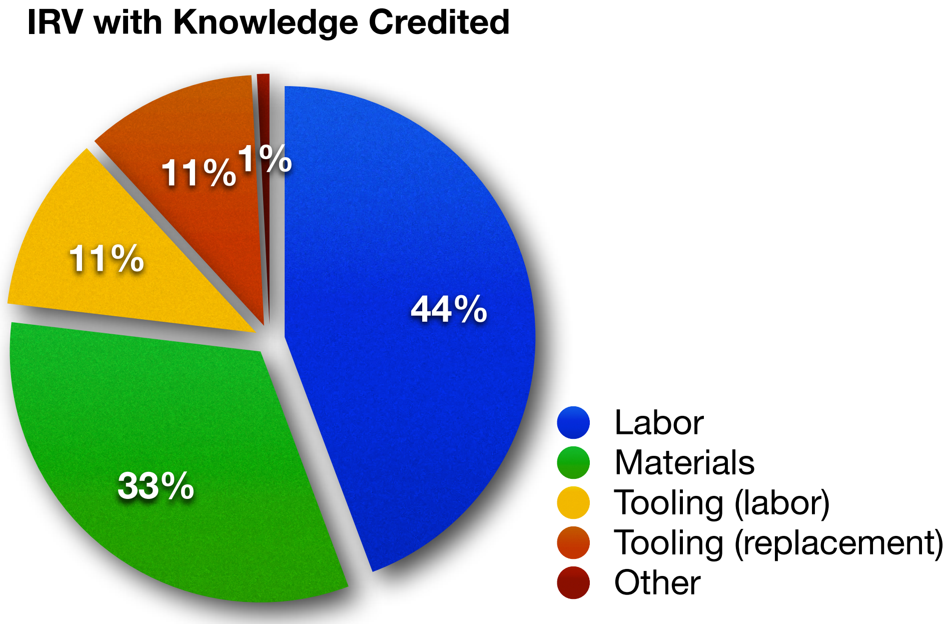

Figure 5-3: Assuming Credited Knowledge, Production Cost Breakdown of the FOAK IRV by Cost Drivers.

Cost Driver	% Cost of Component	Error as % of Total IRV
Material	33%	±4%
Labor	44%	±3%
Tooling Labor	11%	±<1%
Tooling Replacement	11%	±0%
Other	1%	±0%
Total	100%	±7%

Table 5-3: Assuming Credited Knowledge, Cost Contribution and Error by Cost Center as % of total IRV cost

increase in labor cost was due to the uneven shrinking of the production cost due to differing learning rates of different manufacturing processes throughout the model. Clearly reduction in these labor and materials costs, significantly reduced the production costs of the IRV.

Figure 5–4 and Table 5–5 show the cost breakdown of the FOAK IRV in terms of the Pressure Vessel, Reactor Core, Steam Generator, Control Mechanism, Coolant Pumps, and Pressurizer. The two dominant contributors to the cost of the FOAK plant remain the Pressure Vessel and the reactor core. The relative contribution of the two components has significantly changed. The pressure vessel which

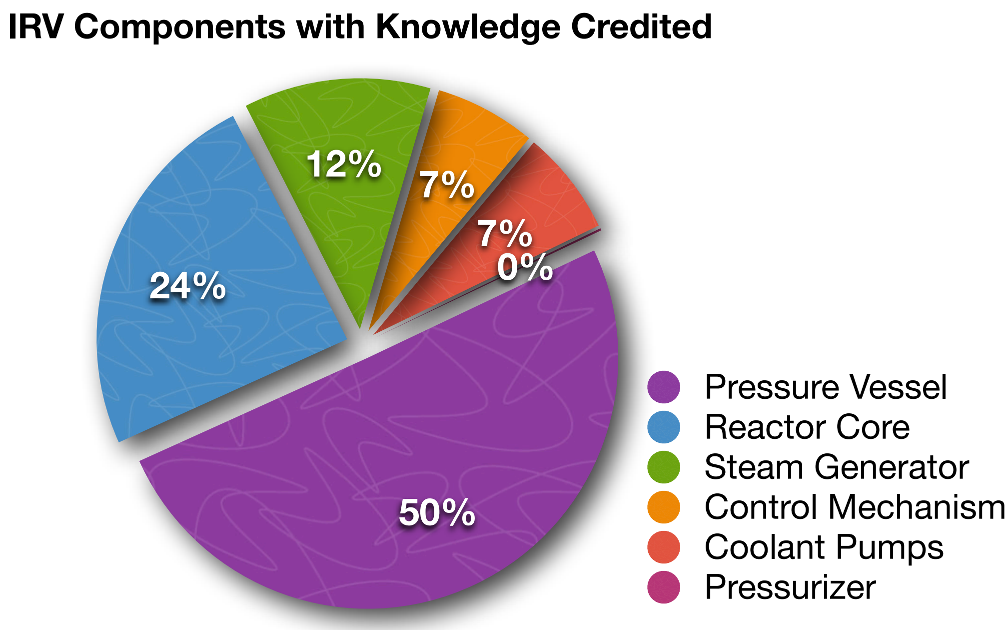

Figure 5-4: Assuming Credited Knowledge, Production Cost Breakdown of FOAK IRV by Components

Cost Driver	% Cost of Component	Error as % of Total IRV
Pressure Vessel	50%	±3%
Reactor Core	24%	±2%
Steam Generator	12%	±1%
Control Mechanism	7%	±<1%
Coolant Pumps	7%	±<1%
Pressurizer	<1%	±0%
Total	100%	±7%

Table 5-4: Assuming Credited Knowledge, Cost Contribution and Error by Components as % of Total FOAK IRV Cost

did not have much prior learning credited increased from 39±3% of the total cost to 50±3%. The high learning attributed to the fuel assemblies as discussed previously has caused this component to fall to 24±2% from 32±2% of the total IRV cost of the FOAK unit.

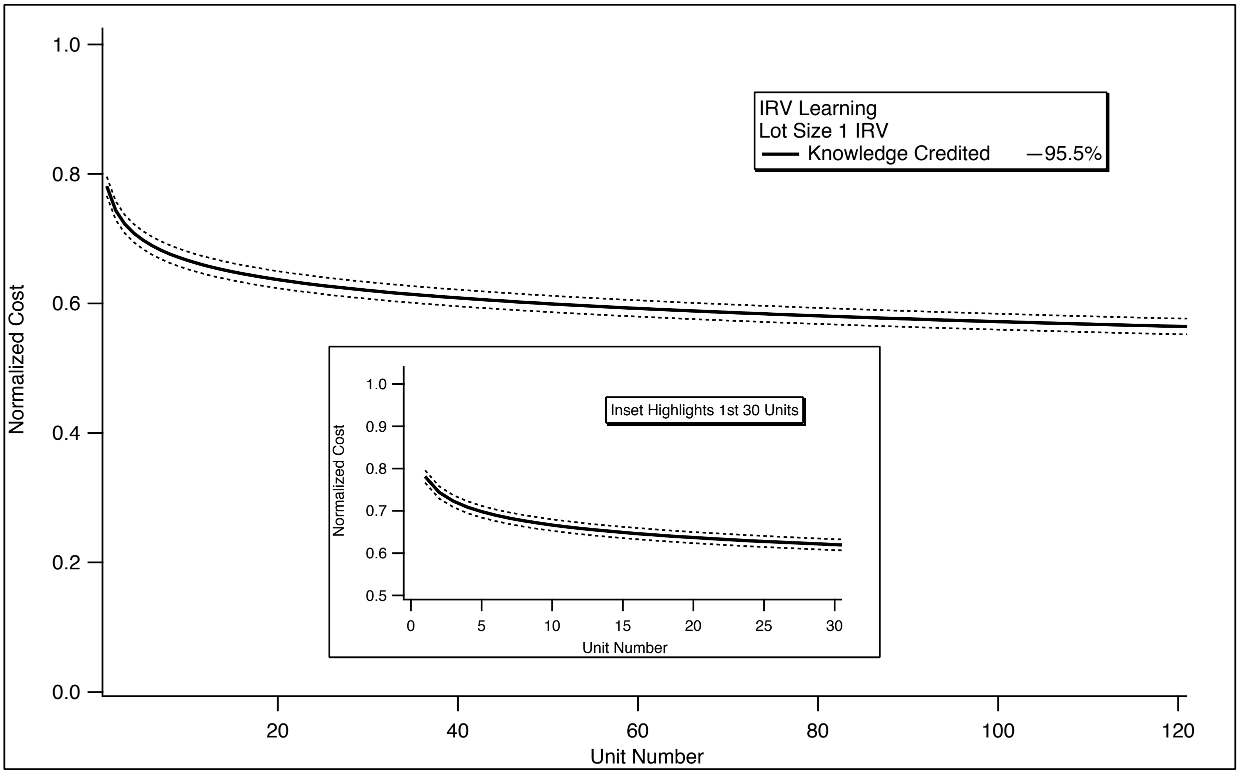

Figure 5-5: Learning Curve for the FOAK IRV Showing the Effect of Prior Learning

The learning curve for the the FOAK IRV with transferred knowledge from prior learning clearly demonstrates the reduction in cost as compared to the FOAK IRV (Figure 5-5). The cost of the FOAK IRV as presented there was normalized to the cost of the LEAD IRV. Therefore, the cost of the first unit was not equal to one. The largest effect of crediting pre–existing knowledge was that the FOAK cost was 78% of LEAD cost. This was a significant reduction and knowledge transfer must be considered when determining the lot size needed to ensure a factory manufacturing environment exists for the nascent SMR industry.

ii.) FOAK Cost Estimates with Full Transfer of Prior Learning

There is a limit to the amount of learning that can reasonably be incorporated at the outset of production. However, from the perspective of a computer simulation, there are no limits. It was possible to simulate the effect of perfect learning transferral, and the effect this has on the absolute cost of the FOAK and the learning rate. For the sake of establishing a bounding case for the effect of transferable knowledge, a model has been developed which assumes that any prior learning is perfectly transferred. Another way of thinking about this is that it is the learning to be expected if one could start by building a NOAK unit.

As before, the reactor core and steam generator enjoy the benefits of transferred learning. However, now the other components must be reevaluated for their potential gains from prior learning. Before, it was stated that too few reactor pressure vessels were manufactured for there to be a guaranteed effect from prior learning. In reality, Japan Steel Works has produced 80 pressure vessels sing the materials and design that would be consistent with a reactor pressure vessel [JSW, retrieved 2012a]. In the case of the control rods in the control mechanism, the reasons for abstaining from applying the effect of prior learning are no longer considered. There have been 5000 control rod bundles produced to date by Areva [Areva, retrieved 2012a]. The control rods manufactured by are similar in construction to those used in the generalized IRV control mechanism. Areva also manufactures GW-scale reactor coolant pumps. Because the generalized IRV coolant pump design is a scaled down version of the full scale coolant pumps, the learning gained from producing 220 coolant pumps was also applied [Areva, 2012]. Applying the full transfer of learning is difficult in practice due to the origin of some of the prior learning: in countries such as Japan and France as it is difficult to perfectly transfer learning even from within the same factory, to which the study of "unlearning" can attest. The purpose of this exercise was to illustrate an extremum of the model parameters which shows the limit of the learning model.

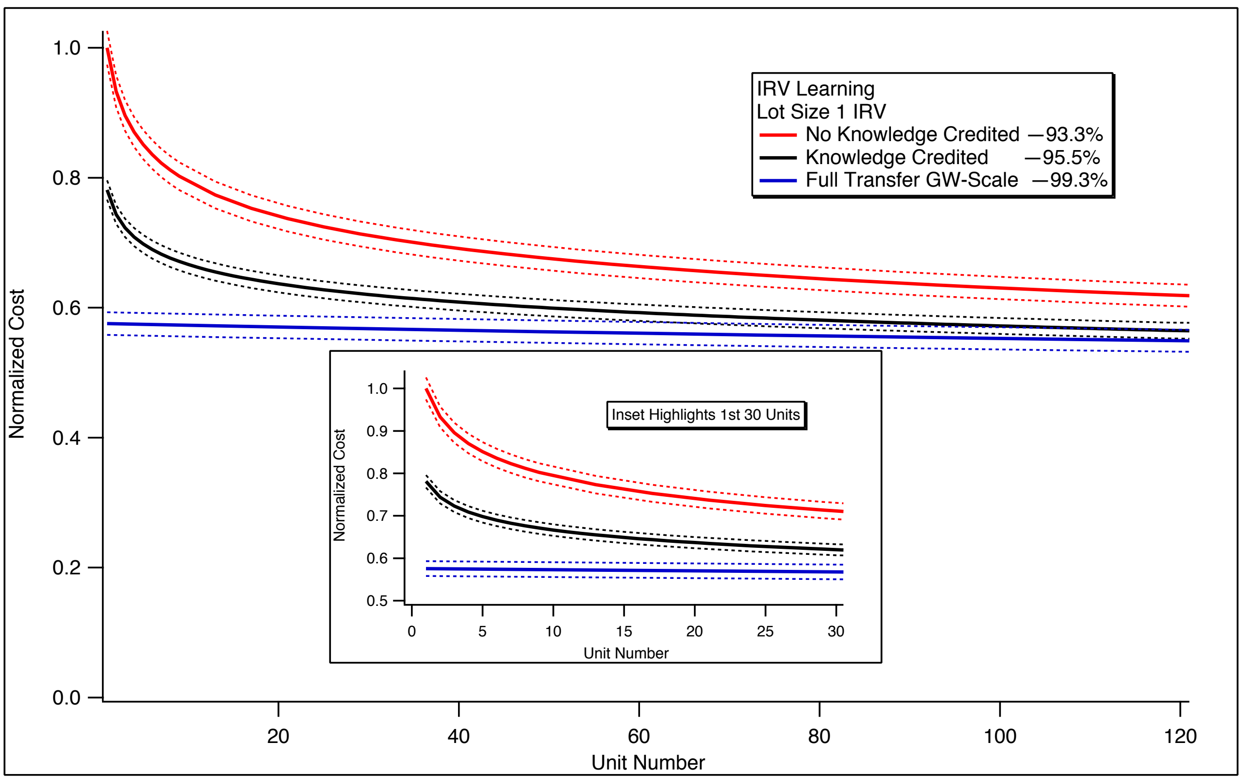

Figure 5-6: Learning Curve Comparing LEAD, the FOAK with Partial Knowledge Transfer, and FOAK with Full Knowledge Transfer

The effect of totally transferring knowledge was to develop an extreme bounding case on the FOAK IRV design. The initial cost of the first unit, under the assumption of complete learning transfer, reducing the initial cost to 59% of the cost of the LEAD IRV, and 76% of the FOAK with more appropriate levels of transferred knowledge. The learning rates also showed interesting behavior. In the case of the LEAD IRV, the learning rate was found to be 93.3%, and in the case of the FOAK with transferred learning, the learning rate was 95.5%. However, in the case of the complete transfer of learning, the new learning rate is 99.3%, which shows essentially zero learning.

F. Conclusion

From the learning curves in Figure 5-6, the LEAD learning curve provides an upper limit on the learning rate whereas the extreme case of complete knowledge transferral from prior learning provides a lower bound on the learning rate. Therefore, the simulations of the LEAD, FOAK, and FOAK with extreme transferral of prior learning, serve as a range of values wherein the actual value of the IRV manufacturing industry learning rate is likely to be found. This learning rate is expected to be near to 95.5%, but fall within the range between 93.3% and 99.3%. In fact, different manufacturers of SMRs are likely to be able to transfer different amounts of production knowledge due to different experience levels with each of the manufacturing techniques and reactor IRV components. Therefore, it is possible that nearly any curve of learning rate between these two bounds could be observed. It is still expected that a learning rate of approximately 95% would be a reasonable value to use for SMR project planning.

By calculating a learning rate at or near 95.5%, the manufacture of SMR IRVs would have a lower rate of learning than any of the allied industries, which are closer to 85%. A few possible explanations are can be proffered. It is important to consider that the model only simulates the manufacture of the IRV and does not consider the construction of the remainder of the plant facilities. This on site construction is fundamentally a manual operations and therefore will experience higher rates of learning which would partially offset the lower rates of learning in the manufacture of the IRV. This offset would not necessarily increase the overall learning rate of the SMR industry to 85%, but it would likely bring it closer to this figure. Another possible explanation for the discrepancy is that the learning rates reported by the aircraft and shipbuilding industries include older values when manufacturing involved more manual labor. When the aircraft industry's learning rate was determined, there was little robotic automation. Whereas the learning rate of the electronics industry (90-95%) is partially dependent on much higher levels of automation, and is consistent with the learning rates of the IRV LEAD learning rate (93.3%).

The learning rates of the allied industries also include values from when there was little opportunity to apply any prior learning. Whereas, in the model discussed in this paper, even in the LEAD case, process knowledge now exists in many areas. The high levels of automated manufacturing and the existence of prior knowledge due significantly reduce the expected learning rates that will be observed in the production of IRVs in the Small Modular Reactor industry.

VI. Factory Manufacturing Environment

When considering the economic case of IRV manufacture, the size of the order book is a quantity of interest because it partially determines the viability of a market for SMRs[Brahimi, 2006]. The minimum lot size necessary for IRV manufacturing is the number of IRVs a buyer or buyers would order to best take advantage of the IRV factory environment, and gain the greatest benefits therefrom [Okhrin, 2011]. The production cost for a single IRV is estimated to be in the hundreds of millions of dollars[Fairley, 2010]. Therefore, if the minimum lot size needed to sustain the layout changes, equipment upgrades, process refinements, materials costs, and labor pool are large, then the cost will be prohibitively high and therefore demonstrate the impracticality of SMR manufacture.

A buyer may define their order to meet their power generation needs, while simultaneously meeting their budgetary limitations. The result should be that the order size should allow for the slight variation of the demands of a buyer [Porras, 2005]. It may even be beneficial to encourage multiple buyers to pool their orders to reach the necessary lot size that keeps the factory environment viable. For the vendor, a decrease in orders below the needed lot size would mean an increase in the average cost of production for each IRV. It must be the case that a slip from one order to a slightly smaller order does not change the economics significantly [Wosley, 1995].

A. Lot Size and IRV Cost

The concept of the order size is predicated on the mechanics of industrial manufacture. It is understood that in a factory environment, a given product is often manufactured in batches known as lots [Anderson, 1993]. Lots are defined by the functional nature of factory operation. Specifically, a factory is assumed to maximize efficiency and minimize production cost. As stated in the previously, this phenomenon is described by learning curve theory. Apart from direct learning related to touch labor, there are institutional changes to the factory environment which maximize efficiency and minimize production costs. However, such changes are not smooth, often consisting of factory layout changes, upgrades in equipment, or other process refinements which cannot be practically implemented on-the-fly [Schneider, E.A., 2008]. To limit the disruptions to production, these changes take place between lots. It is in this way that lots are functionally defined: as the number of units produced in a factory between successive implementations of process refinements.

The implementation of these refinements can be understood as the combination of two factors: the cost of implementing the refinements, and the subsequent reductions in production cost bought by these refinements. The cost of implementing these refinements is distributed over the production cost of the units in all subsequent lots as is the reduction in production cost bought by these refinements. However, where the reductions in cost are reasonably considered to be continuous, the application of the process refinements is, by definition, discontinuous. Given that the learning model is predicated on continuous learning [Wright, 1936], or at least a near approximation thereof, this could pose a problem. However, due to the discrete data sets produced by SEER–MRG[SEER, 2011], this problem is avoided. Each lot is simulated by SEER using the parametric model of the IRV design and the applied learning rates consistent with the LEAD, FOAK, and FOAK with total transfer of prior learning. The program begins by running the Monte Carlo simulation for each unit in the lot and then determines the average cost per unit in that lot. This process is repeated for each lot to be produced. In this way, the average cost per unit in a lot of N units, for X total units produced can be determined. In addition to the reductions in production cost brought about by these refinements, the typical learning effects are still at work. This results in a change in the learning rate for production in lots consisting of greater than one unit. The lot midpoint iteration method, detailed in Appendix A, was used to determine these new learning rates.

For the LEAD, FOAK, and FOAK with total transfer of prior learning, production runs in lots of 1-12 were conducted over 120 units. By examining this range of lot sizes, a wide range of production configurations could be explored to determine if there was a measurable gain either in the absolute production cost, or in the learning rates, as a result of production in lots. One hundred twenty units represented a 12 GW fleet of SMRs which provided for an adequate sample for simulation.

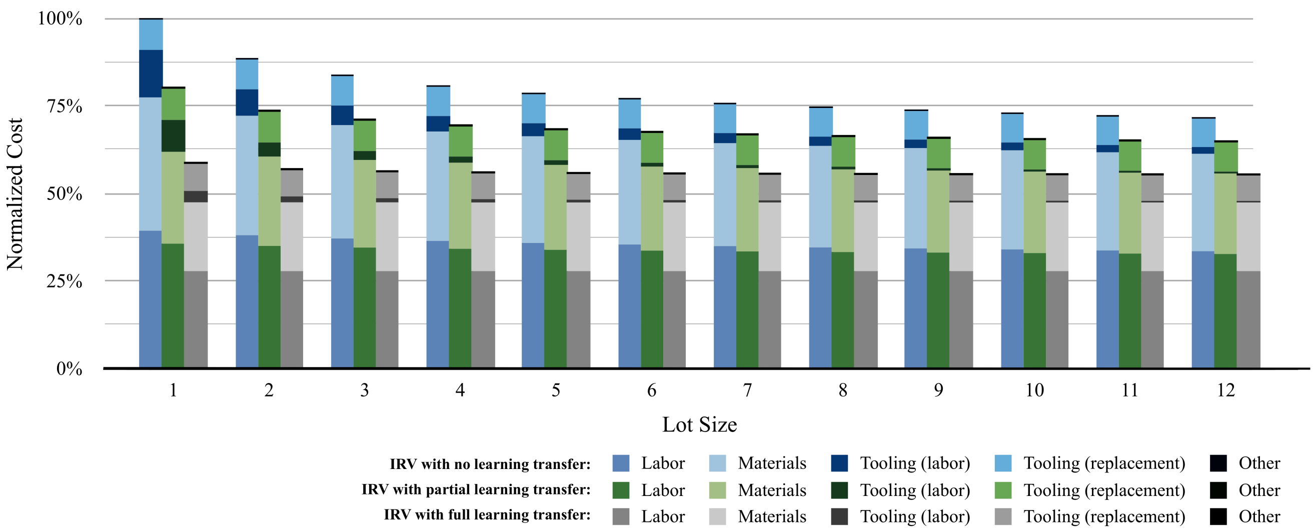

Figure 6-1: IRV Production Cost by Cost Center and Lot Size for LEAD, the FOAK with Partial Knowledge Transfer, and FOAK with Full Knowledge Transfer

The production costs were normalized to the absolute cost of a LEAD IRV produced in lots of 1 unit. The results of the simulations in Figures 6-1 and 6-2 show the relative production costs of the LEAD, FOAK, and FOAK with full transfer of prior learning. The blue data sets, corresponding to the LEAD IRV, show the reduction in average cost per unit as the lot size increases. The green data sets, corresponding to the FOAK with credited knowledge, also show the reduction in average cost per unit as the lot size increases. The data sets in grey correspond to the full transfer of prior learning in the FOAK IRV. Because of the extreme transfer of prior learning, the extent to which production in multiple lot sizes could demonstrate a change in average production cost reduction was severely constrained. Again, it is important to reiterate that this data represents the lower bounding case of learning in IRV production.

The data in Figure 6-1 demonstrates the amortization of the cost of tooling labor over the increasing number of units in each lot. This can be understood as a consequence of the definition of the lot size. The cost of the labor required to retool the machinery, rearrange production processes, and institute other production process refinements, depends on each instantiation of these tooling activities. By increasing the number of units per lot, the number of units affected by the tooling activities increases. This effectively divides the tooling labor among the units in the lot, leading to a reduction in the dependance of the average unit cost on the cost tooling labor. Practically, this means that a factory worker is required to do less labor related to tooling activities per unit, allowing the vendor to absorb the difference in tooling labor cost as savings. The contribution to the average total cost of the tooling labor is nearly proportional to the inverse of the lot size. In lots of two units, the tooling labor is almost halved from what it was for lots of one unit. Whereas, in the lots of three units, the tooling labor is nearly a third of the tooling labor for lots of one unit. This is true in both the LEAD and FOAK designs, and holds true up until the lot size increases above six units. Beyond six units per lot, the degree to which the tooling labor cost can be amortized reaches a limit set by the other costs wrapped up in the tooling labor. These other costs include tool breakage, and replacement due to wear and their associated labor costs. These costs increase as the number of units increase.

Apart from the tooling labor cost, Figure 6-1 shows that the other major driver of cost reduction in IRV production occurs within the non–tooling labor cost, with little learning seen elsewhere. The reduction in the cost of labor as a function of lot size is the result of learning during the production of units within a single lot. If each lot can be seen as a production run consisting of the number of units in the lot, produced one at a time, then reductions in labor cost result from standard learning-by-doing. When comparing the LEAD and FOAK designs, it can be seen that despite the LEAD seeing larger reductions in the absolute cost as the lot size increases, at all lot sizes, the FOAK design is less costly. In fact, to achieve the same average cost per unit as the single unit FOAK lots, the LEAD must be produced in lots of six units.

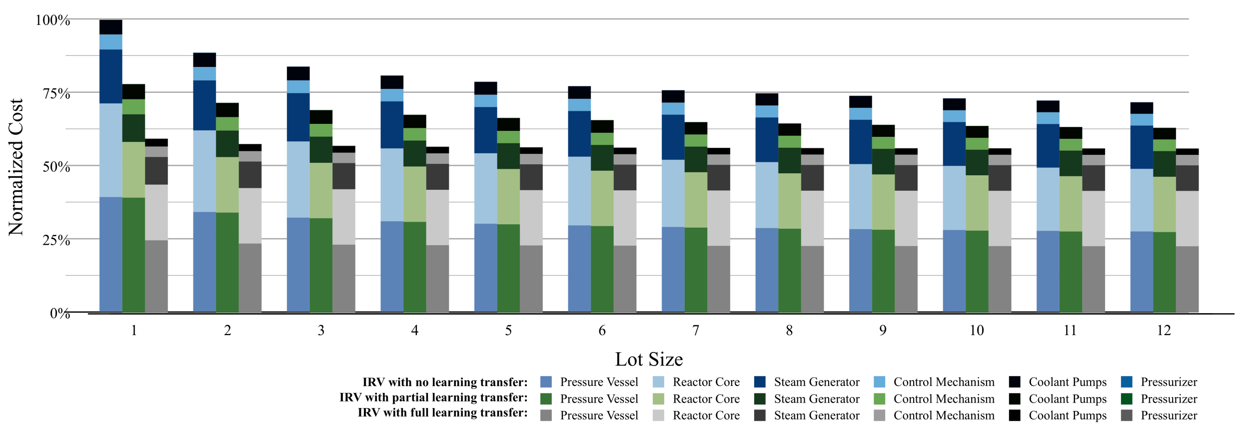

Figure 6-2: IRV Production Cost by Component and Lot Size for the LEAD, the FOAK with Partial Knowledge Transfer, and FOAK with Full Knowledge Transfer

It is possible to see the relative cost contribution of each of the physical components of the reactor to the total cost of the IRV model in Figure 6-2. The largest improvements from increasing the lot size come from the reactor vessel. It can be seen that as the lot size increases the LEAD and FOAK designs converge on the same relative cost breakdown between the physical reactor components. In this case, the FOAK with full transfer of prior learning appears to be the limit of this convergence.

This result is consistent with the understanding that the major components, though making up a larger portion of the total cost, consist of many different subcomponents, and can therefore be seen as collections of lots of their subcomponents. Therefore, there would be less opportunity to benefit from increases in lot size. This is evident when considering either the reactor core, or the steam generator. In the case of the reactor core, the assemblies can be seen as lots of 264 rods, and the associated components. Following the trend seen in Figures 6-1 and 6-2, beyond a certain point, increasing the lot has diminishing returns on the reduction in production cost.

In contrast to the reactor core and the steam generator, the reactor vessel is a single unit. Therefore, there is no internal manufacturing benefit from production of multiple components as observed in the steam generator and reactor core. This suggests that a focus should be made on the manufacture of the reactor vessel. The pressure vessel will be made in the smallest quantities and any cost savings in the initial manufacturing will likely play a larger role in reducing overall IRV manufacturing costs. Reactor vessel manufacture in lot sizes >1 will also yield a greater return on investment than for any of the other components.

In general, it is clear that increasing the size of the lots produces a reduction in cost. However, there is a point beyond which the gains in producing larger lot sizes are diminished to the point where increasing the lot size is no longer advantageous to either to the vendor or the buyer. This point defines what is called the minimum order size [Okhrin, 2011]. The minimum order size will be discussed in the following section. It is interesting to note that from comparing Figures 6-1 and 6-2, it is evident that the three learning models of IRV production begin to approximate the same configuration in total cost, cost driver breakdown, and component cost breakdown, between the 3 models of IRV production, as the size of the lots increases from 1 to 12. The configuration of this convergence can be considered the NOAK IRV cost structure at lot sizes exceeding 12 units.

In addition to the reductions in the average cost of production resulting from increasing the lot size, there is an additional effect produced in the learning rates for the average cost. The learning rates increase as the lot size increases or the reduction in the average production cost of an IRV decreases. This effect is consistent across IRV models, though not by the same levels. At one unit lots, the learning rates range over 93.3% for the LEAD, 95.5% for the FOAK, and 99.3% for the FOAK with full transfer of learning from prior knowledge. For twelve unit lots, the learning rates range over 96.5% for the LEAD, 98.8% for the FOAK, and 99.3% for the FOAK with full transfer of learning from prior knowledge. In each case, the rate of production cost reduction is diminished as the lot size increased. Despite the effect of dampening the effective learning rate, the benefit of overall reductions in the average production cost per unit for an increase in the lot size offsets is substantial.

Consider the case of a FOAK produced in lots of one unit. Using a learning rate of 95.5% the cost of producing ten units is 107% of the cost of producing two lots of five units with the learning rate of 97.8%, and 110% the cost of producing ten units in a single lot of ten units. This suggests that arbitrarily large lots yield arbitrarily large reductions in cost, but this is an artifact of the assumption of continuous and infinite learning. Reality constrains this prediction in at least three ways: First, learning does not, in practice, continue forever. Second, even though a lot of 1000 units may reduce the average cost per unit by a very appealing amount, the absolute cost of producing this many IRVs at one time would make this extremely cost prohibitive. Finally, there are limits as to how much IRV production can be accommodated by a physical factory. This study assumed the existence of a dedicated vendor factory with facilities as large as necessary to manufacture a given IRV production configuration. Realistically, no factory could produce 100 IRVs simultaneously.

B. Size of the Lot Needed To Maintain Efficient Manufacturing

The purpose of the simulations of multiple lot sizes, using the three learning models, was to determine the minimum size of a lot needed to maintain an efficient factory environment. While the model that was setup for this study can include throughput, fixed factory and licensing costs, and the cost of money, these items were left for exploration in future studies.

With the results obtained through the Monte Carlo simulation, it was possible to determine the best lot size using the following conditions. The primary condition restricting the lot size is the rate at which the production cost reductions from one lot size to the next become indistinguishable. Stated differently, if the average cost of a unit in the N^{th} lot differs from the average cost of a unit in the $N+1^{th}$ lot by an amount that is very near to the difference between average cost of the $N-1^{th}$ lot and the average cost of a unit in the N^{th} lot, then this condition is met. To better illustrate the changes of an increase in an order of a particular lot, the differences in the average production cost from one lot to the next were graphed, and then linear fitting was performed to determine the inflection point (Figure 6-3). The inflection point indicates a change in the behavior of production cost reduction occurs just below an order size of 5 units. Between lots of one unit and lots of five units, there is a steep drop in the difference between lot average costs. Lot sizes of greater than 5 units see a much slower drop in the difference between lot average costs. In fact, the differences approach the limits of the accuracy of the model. The lot size of five marks the boundary between two regimes of production cost behavior where the regime consisting of lots greater than five units optimize the economics of factory production for the vendor. Therefore, the minimum order size which preserves the factory environment, is 5 units.

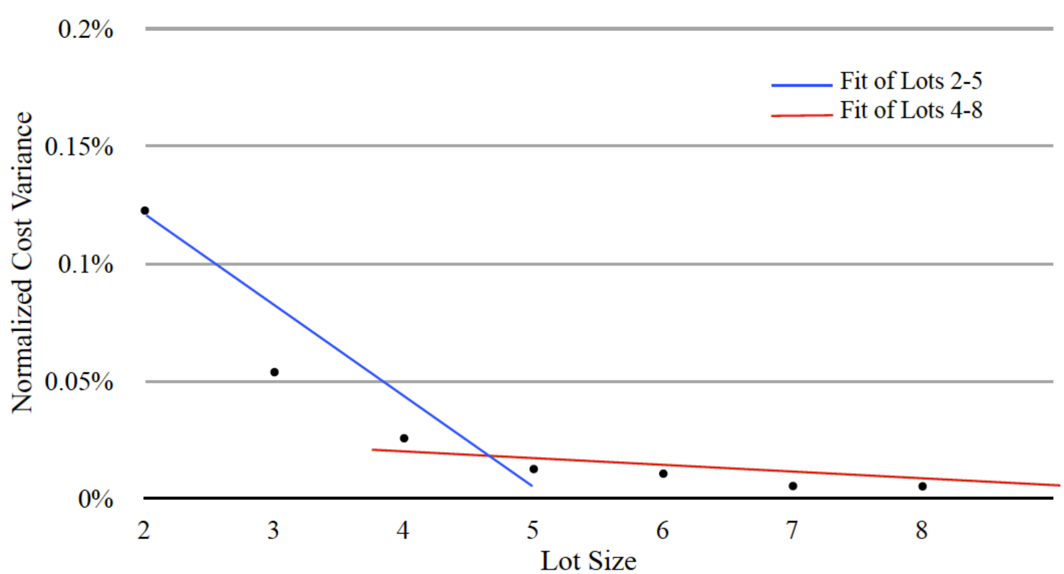

Figure 6-3: Percent Reduction in Production Cost Based on Ordr

Figure 6-4, shows the effect of learning on the FOAK model produced in lots of 1 and the minimum lot size of 5 unit lots, normalized to the cost of producing one LEAD IRV in a lot of one unit. It is important to note that though these data sets share the x-axis, the x-axis means something different for each set. In the case of lots of 1, the numbers on the x-axis correspond to the actual unit number, and the y-values are the normalized production costs for that unit. In the case of lots of 5 units, the x-values are the number of the lot, and the y-values correspond to the average cost of an average unit in that lot. Therefore, the total number of units produced for the lot size of one is fifteen, whereas the total number of units produced for the lot size of five is seventy five. Here, the effects of learning show that for a lot size of 5 units, the average production cost is lower than for that of a lot size of 1 unit. Looking specifically at the labor cost, these values seem to converge on an absolute value after fifteen units are produced in lots of five units. Whereas the labor cost in lots of one continues to decrease until ten units have been produced in lots of one. This reinforces the idea that the learning rates are greater in lots with fewer units. The same sort of behavior can be seen in the materials and the tooling replacement. The main difference in costs lies in the tooling labor. Similarly to the effect discussed in the comparison of individual lot comparisons, the tooling labor decreases as a rate that nearly matches the increase in the number of units per lot. Here it can be seen that this reduction is preserved even after many units have been produced. Looking at the first lot of five units, the tooling labor is nearly one fifth that of the tooling labor in the lot of one unit. This relationship is preserved even up to the fifteenth lot of five units, and the fifteenth lot of one unit. It is important to note that at the eleventh lot of five units, the tooling labor stabilizes and decreases by amounts which are below the threshold of the error in the cost estimates. This effect cannot be seen in the production of IRVs in lots of one unit

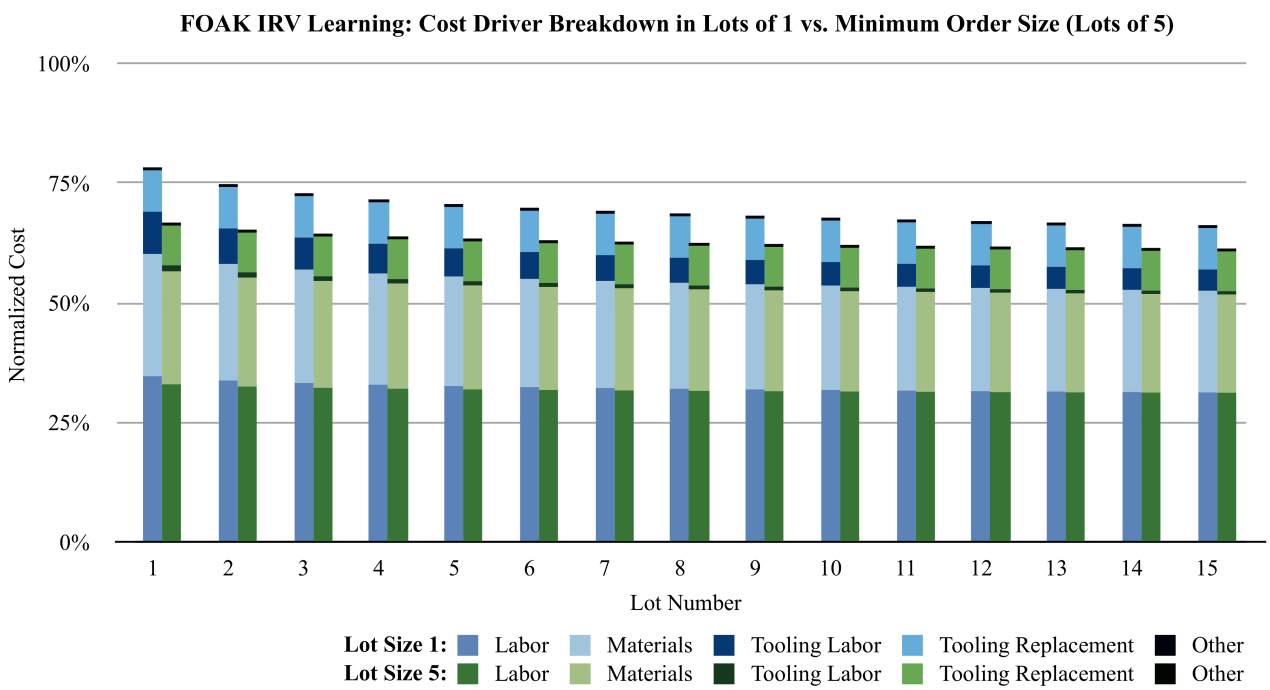

Figure 6-4: FOAK IRV Learning by Cost Center for Two Lot Sizes for First 15 Lots

because fifteen units is not enough to see the reductions in tooling labor cost stabilize.

In Figure 6-5, the production of the FOAK IRV in lots of one and five units is compared as broken down by the physical components comprising the IRV. Focusing on the pressure vessel, it is clear that the largest reductions in production cost originate in this component, and that this result (originally obtained from the simulations in lots of one unit) is preserved when production increases to 5 units per lot.

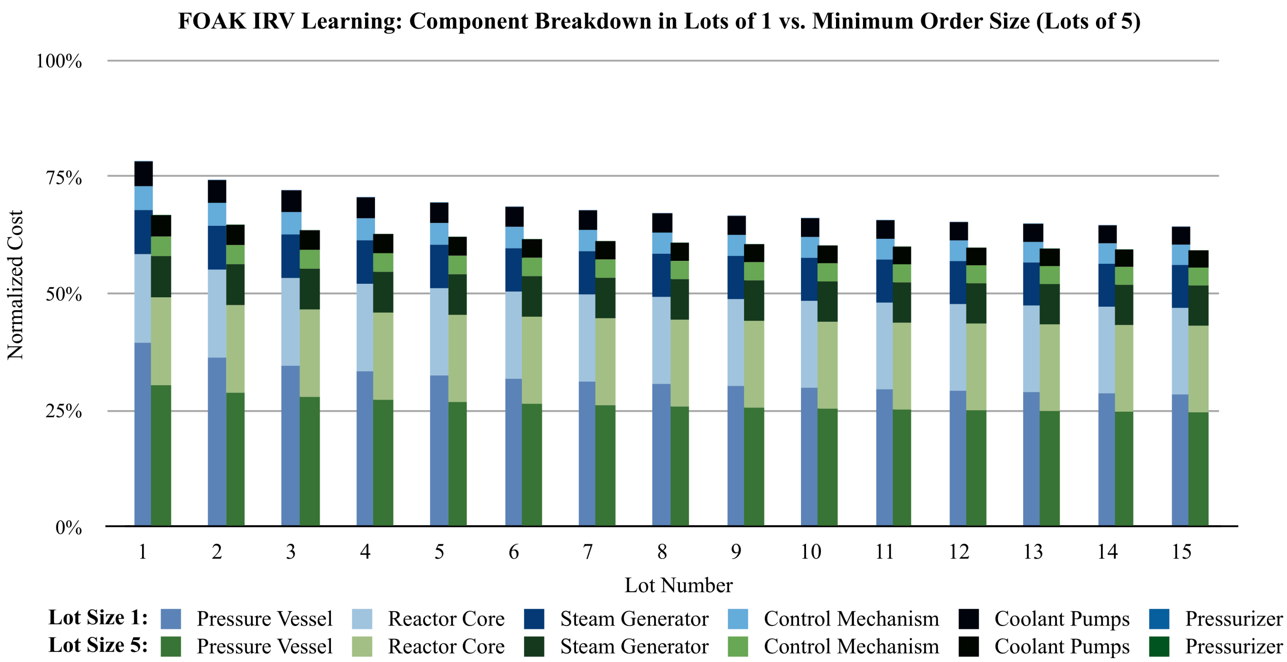

Figure 6-5: FOAK IRV Learning by Component for Two Lot Sizes for First 15 Lots

After the pressure vessel, the next largest reduction in production cost comes from the coolant pumps, though, this reduction is mainly visible in production in lots of one unit. The disappearance of significant learning in the coolant pumps is worth discussing. It was stated, when defining the process by which knowledge is credited, that some components include large numbers of duplicate subcomponents, e.g. steam tubes in the steam generator. The production of duplicate components is subject to learning. Given that the learning is traditionally modeled using the log-linear learning curve [Wright, 1936], the reduction in cost is sensitive to unit number. The unit numbers for the duplicate components grow much faster than the unit numbers of the components of which they are a part. As a result of this, the duplicated components converge to their equivalent NOAK production regime well before the complete unit reaches its NOAK cost. According to the generalized 100 MWe IRV design discussed in Chapter IV, the IRV includes 8 coolant pumps which experience effective learning at a much faster rate than the total IRV. Therefore, in each production configuration, the cost of the coolant pumps converges to an NOAK state in fewer IRV units than does the total IRV. It is possible that this early convergence is partly responsible for the inflection indicating the minimum order size.

The minimum value for the lot size has been determined to be 5 units, however, in the interest of minimizing the risk of cost increases to both the vendor and purchasing utilities, it is advisable that the minimum lot size be increased to 6 units. Increasing the number of units in the lot from 6 to 7 only yields a reduction in the average cost of a unit of < 0.1% regardless of the IRV model. Decreasing the number of units in the lot from 6 to 5 also yields an increase in the average cost per unit by <0.1%. Both of these margins are below the sensitivity of the model to distinguish the production costs. Therefore, there is no measurable difference between these production configurations. A lot size of 6 units constitutes an optimal configuration which limits risk and maximizes flexibility within the manufacturing conditions postulated within the model. Finally, for a production configuration of a 6 unit lots, and using the FOAK with crediting knowledge as the most realistic representation of IRV production, the expected learning rate is 98.1% with an initial average production cost of 66% of the LEAD model. If the learning rates of the LEAD and the FOAK with full transfer of prior learning can be treated as bounds on the learning rate in the FOAK with credited knowledge, then the range of learning rates for a lot size of 6 units is expected to fall between 95.5% and 99.3%.

VII. Conclusion

The purpose of this work was to investigate the nature of SMR economics. This was achieved by focussing on the factory setting manufacture of a generalized IRV design. The generalized design was based on the specific systems of pressurized water reactor technology and the common traits of the main SMR vendor IRV designs. It was determined that the IRV would be composed of a reactor core with a total power output of 100 MWe. The basis for the control mechanism, i.e., the control rod and drive mechanism, would be based on traditional designs despite the understanding that the designs likely to be implemented by the SMR vendors would be based on more novel technology[Yang, 2007]. The IRV also includes a steam generator implementing a once-through straight tube design, which was consistent with the higher power output IRV designs put forth by Westinghouse and Babcock and Wilcox [Westinghouse, 2011][Babcock & Wilcox, 2012]. Eight coolant pumps are utilized in the IRV to circulate the primary coolant. A pressurizer based on those used in AP1000 reactors was incorporated into the pressure vessel which enclosed the reactor core, control mechanism, and steam generator.

The generalized IRV design was manufactured in an SMR vendor factory setting which was assumed to be a specially designed, dedicated factory for the fabrication of all of the components. As with the vendor factory, all purchased parts and raw materials would be sourced local to the United States. The manufacturing processes themselves were modeled to match as closely as possible those processes which are utilized in related, allied industries. Results of the simulations showed the breakdown of the production cost of the LEAD IRV to be 38%±2pts in materials, 39%±3pts in labor, and 14%±1pt in tooling labor with a total error of 6% in the total production cost estimate. By component, the breakdown was found to be 39%±3pts for the pressure vessel 32%±2pts for the reactor core, 18%±1pt for the steam generator, 5%±<1pt for the control mechanism, 5%±<1pt for the eight coolant pumps, and <1%±0pts for the pressurizer. This showed that the pressurizer is a tiny portion of the cost of the IRV and that it was less than total error in the estimate in the LEAD IRV production cost, and could therefore be ignored as a negligible contribution to SMR economics. The resulting model yielded production cost estimates for the LEAD IRV which would form the basis for all of the subsequent modeling, including the application of crediting knowledge, and ultimately the optimal lot size for manufacturing.

A. Learning in Nuclear Construction

The initial production cost estimates formed only the first phase of developing an understanding of SMR economics. One of the most important quantities sought after in this study was the learning rates expected in the manufacture of IRVs. To obtain a learning rate that would be relevant to the economic investigation, it was necessary to develop the parameter space for the learning rates in each of the constituent fabrication processes, and then to use this information to develop an overall learning curve for the LEAD cost estimate. Based on the manufacture of one IRV at a time, the learning rate in the LEAD IRV manufacture was determined to be 93.3%. However, it is recognized that the model which produces the LEAD plant does not take into account the potential of prior process knowledge. The FOAK model was developed to show the importance of the transference of knowledge due to experience in similar manufacturing industries.

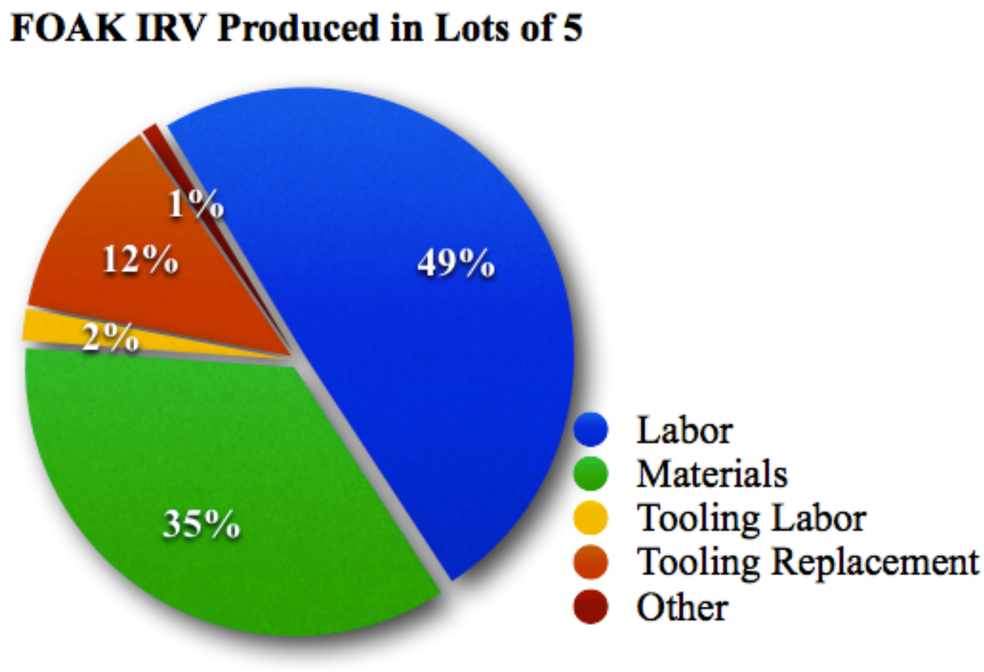

Figure 7–1: FOAK IRV Production Cost Breakdown by Cost Driver for Average Unit in Lot Size of 5 Units

Cost Driver	% Cost of Component	Error as % of Total IRV
Material	35%	±3%
Labor	49%	±2%
Tooling Labor	2%	±<1%
Tooling Replacement	12%	±0%
Other	1%	±0%
Total	100%	±6%

Table 7–1: Total Cost Contribution and Error by Cost Center for Average Unit in Lot Size of 5 Units as % of Total IRV Cost

Developing a model for the knowledge gained from prior industrial efforts, or crediting knowledge, was accomplished by using the existing learning model and modulating a characteristic subcomponent from the IRV which could reasonably be expected to gain from prior learning [Jarkas, 2010]. To determine which components would reasonably benefit from crediting knowledge, each component was compared to their analogous commercial products. Once the analogous components were

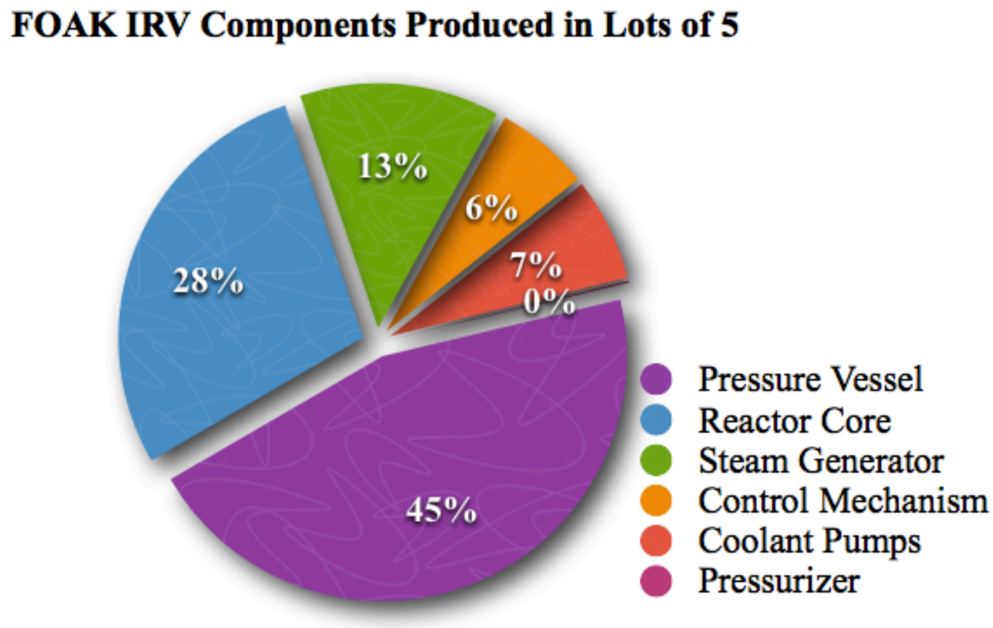

Figure 7–2: FOAK IRV Production Cost Breakdown by Component for Average Unit in Lot Size of 5 Units

Cost Driver	% Cost of Component	Error as % of Total IRV
Pressure Vessel	45%	±2%
Reactor Core	28%	±2%
Steam Generator	13%	±1%
Control Mechanism	6%	±<1%
Coolant Pumps	7%	±<1%
Pressurizer	<1%	±0%
Total	100%	±6%

Table 7–2: Total Cost Contribution and Error by Cost Center for Average Unit in Lot Size of 5 Units as % of Total IRV Cost

evaluated for their similarity to IRV components or subcomponents, the number of each of these components was obtained. From these numbers, it was determined that the fuel assemblies in the reactor core (12,700 units produced) [Ray, 2010], and the steam generator tubes (297 total generators produced) [Babcock & Wilcox, 2012] would benefit most from prior learning. Applying these numbers to the learning model, then recalculating the total IRV cost from these new numbers yielded the effective FOAK IRV production cost figure, which was determined to be 78% of the cost of the LEAD IRV. Using this new production cost, the FOAK unit served as the basis for a new learning curve simulation. The simulations yielded an expected learning rate for the FOAK IRV of 95.5%. An additional case where each component experience maximum transfer of knowledge from prior learning was also considered as a bounding case. The initial production cost of this "NOAK" unit or FOAK with complete knowledge transfer, was determined to be 58% of the LEAD production cost and had an associated learning rate of 99.3%. The total transfer of complete process knowledge is unrealistic, but this case served as an effective limit on both the cost and the learning rate to be expected from a true FOAK IRV.

In terms of the major cost drivers, the biggest source of learning was in the cost of labor, either in the direct labor, or in the tooling labor. This effect can be seen in Figures 6-1 and 6-4. In the case of the labor cost driver, the cost reductions could be understood as a direct effect of learning by doing, and were consistent with the traditional descriptions of learning [Wright, 1936].

Reduction in the tooling labor cost arise from the amortization of the tooling costs over the number of units in a given lot size. Vendor efforts at optimizing production with respect to cost lead to the production of IRVs in batches known as lots. The downtime between lot production is used to institute refinements to the production process, the chief cost of which is wrapped up in the tooling labor cost. Because the process refinements affect all subsequent units, but especially those where production immediately follows the changes, the tooling labor cost associated with these changes is amortized over these units. Lot size production cost dependance leads directly to the idea of a minimum order size which optimizes the benefits gained from this effect.

The physical components expected to experience the most learning, according to the models proposed above, are the reactor vessel and the control mechanism, with learning rates near 93%. The levels of learning predicted are reasonable because in the case of the FOAK learning model, the reactor vessel and control mechanism are both not expected to benefit from prior learning. For the reactor vessel, this is partly due to the low numbers of produced reactor vessels by any single company, and partly due to the redesigns required by the novel SMR IRV. The control mechanism, on the other hand, will be a nearly prototypical subsystem. With the special need, imposed by the IRV designs, that the control mechanism operate completely inside the pressure vessel, the design for the control mechanism will diverge from existing designs [Yang, 2007]. This suggests that it would be inappropriate to expect prior learning to apply as readily as it would to other subsystems. Conversely, the learning rate should, therefore, be higher, because there is much more to learn. However, low levels of learning indicate a dependance on high levels of automation, or other processes which do not allow for increased learning. This is consistent with the generalized design as described in Chapter 4. Under the assumption that the reactor components would be built using as advanced of a manufacturing technology as possible, the components were reliant on highly complex machining with higher learning rates. As Table 5-2 states, the learning rates for automated machining are 90-95% [Ostwald, 1991], which is consistent with the learning rates of the LEAD and FOAK learning models.

B. Order Size

The lot size represents another value of interest when evaluating the economics of SMR manufacture. The order size is the minimum lot size of IRVs that buyers need to place with an SMR vendor to ensure a factory manufacturing environment is maintained. This number must meet the power generation needs, production time requirements, and the budgetary restrictions of the buyer(s). From the perspective of the vendor, the functional definition of the minimum order book is the total number of units ordered at one time that best take advantage of the SMR vendor factory setting while minimizing the variability in average production cost produced by changes to the order made by potential buyer(s). The implicit assumption is that an order placed with the vendor may decrease for various reasons causing an increase in the average production cost per unit. The variation in average production cost per unit is due to a combination of learning effects and production cost redistribution. With the learning rates for the LEAD, FOAK, and FOAK with maximum transfer of knowledge from prior learning, it was possible to determine the optimal lot size for IRV manufacturing.

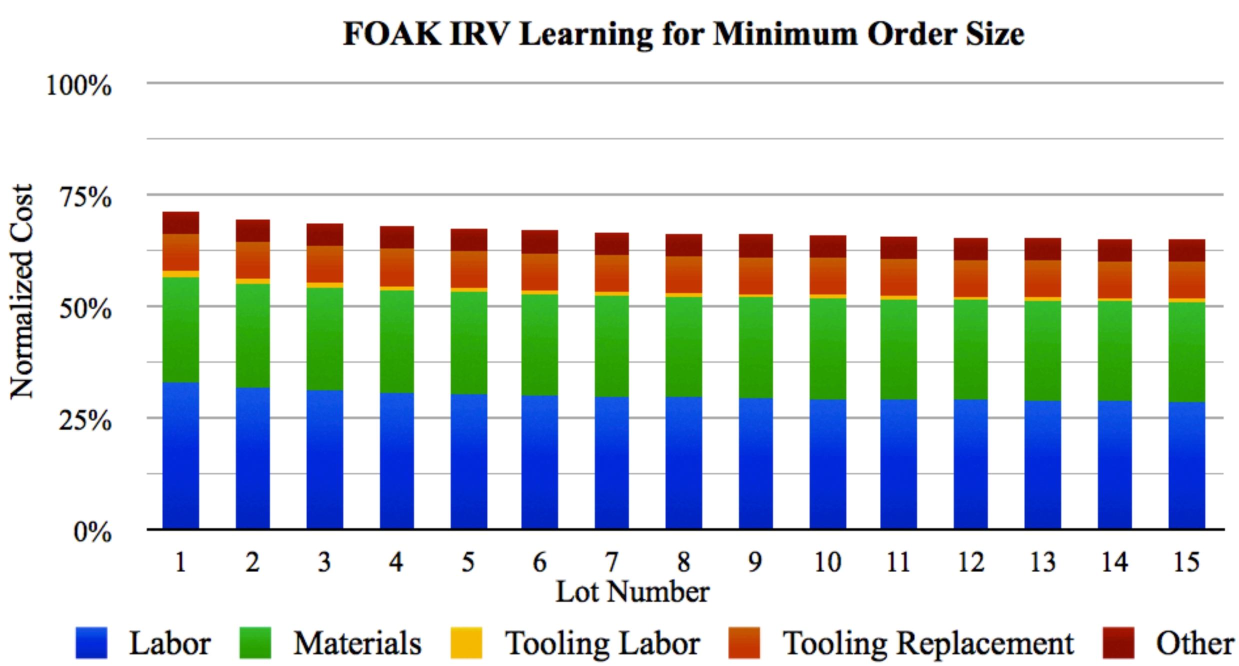

Figure 7–3: FOAK IRV Learning by Cost Center as a Function of Average Unit Cost in Production for a Minimum Lot Size of 5 Units

By simulating different production scenarios, ranging from one unit produced at a time, up to lots of twelve units produced at one time, the changes in average unit production cost were obtained. The change in average cost between adjacent lot sizes was then expressed as percentage decrease of the original cost. Figure 6-3 shows two linear fits whose intersection marks the inflection point characteristic of the transition from large to small differences in average production cost. There was agreement among the three IRV models on the lot size for which this occurs. The minimum order size which preserves the advantages of a factory setting is determined to be 5 units. The cost breakdown of IRV production in lot size of 5 units is given in Figure 7–1 and Table 7–1 for the cost drivers and

Figure 7–2 and Table 7–2 for the reactor components. The effect of learning is depicted in Figures 7–3 and 7–4 for the cost drivers and reactor components, respectively. However, to minimize exposure to production cost increases due to a dropped order, a minimum order size of 6 units is recommended because a drop of an order from 6 to 5 units would only marginally increase production costs by less than 1%. Therefore, producing a FOAK with credited knowledge in lots of 6 units, would have an associated learning rate of 98% at an initial average cost of 66% of that of the LEAD produced in lots of 1 unit.

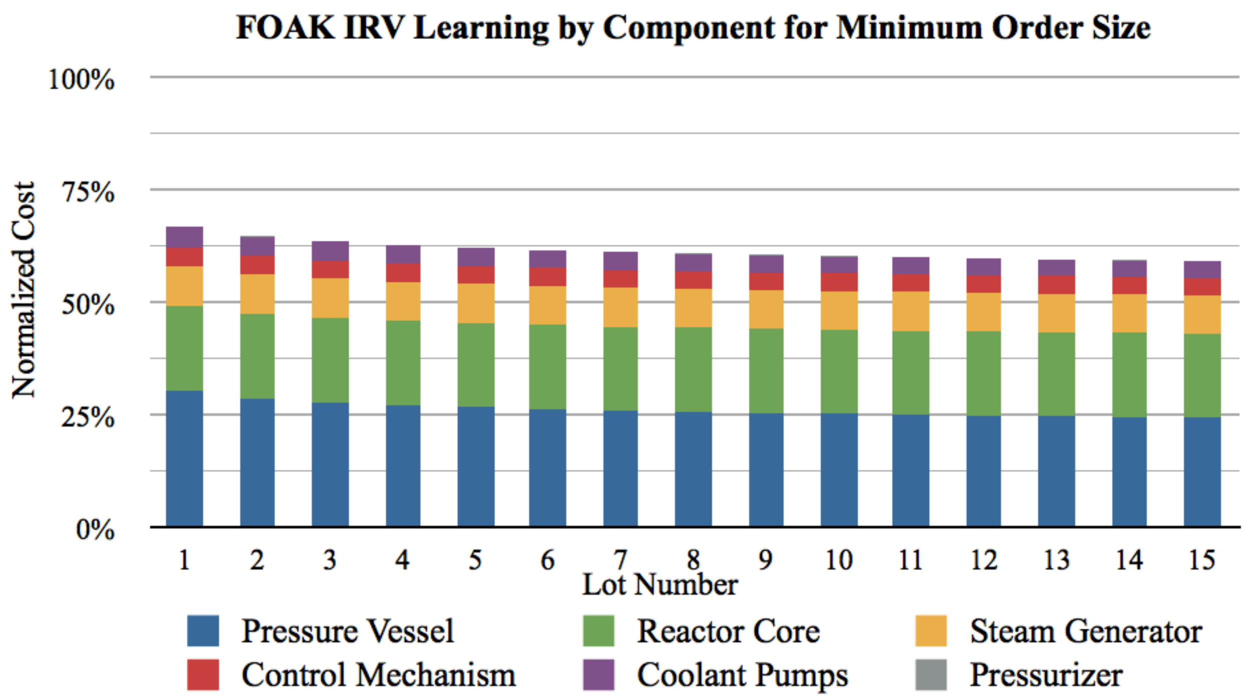

Figure 7–4: FOAK IRV Learning by Component as a Function of Average Unit Cost in Production for a Minimum Lot Size of 5 Units

Consistent among all of the learning models and lot sizes, the pressure vessel is shown to be central to the economics of IRV manufacture, making up 45% of the cost of the FOAK IRV in the case of production in a lot size of 5 units. This component additionally experiences the most learning, and benefits most greatly from the increase in the lot size. Focusing on pressure vessel production will produce the greatest reduction in production cost for the FOAK IRV. The central conclusion from this study is that SMR economics are not likely to experience great reduction in production costs due to learning, as a result of IRV manufacture in a vendor factory setting. Initial reductions in production cost are expected to be observed due to automation in manufacturing and transfer of prior process knowledges. Initial design work of the IRVs should focus on the pressure vessel to try to maximize production processes using automation to minimize the production cost.

C. Focal Points

The simulation suggested the following conclusions will be relevant to IRV manufacturing. The best learning rate was inversely correlated to the best manufacturing outcome, lowest initial manufacturing cost (Figure 7–5). The lowest initial manufacturing cost can be achieved by maximizing the use of process knowledge developed by other industries. The study of allied industries clearly showed that increased use of automation can reduce the initial manufacturing costs. This reduced cost comes at the expense of learning as automated processes have learning rates that approach 100%. The goal of IRV manufacturing must be reduction of manufacturing cost and not the minimization of the learning rate.

Even though the IRVs will be produced in small quantities, many of the individual components making up the IRV are produced in large numbers. The learning in the large production items undergo rapid cost reduction due to learning. The learning for these items takes place during the manufacturing of the first units often within the first lot. The net effect of this is that unit cost reaches its NOAK cost while the learning rate of the component goes to 100%. This results in higher overall learning rates for the total IRV but lower initial costs of the early units. Designs that maximize the use of components that can be produced in large runs will reduce the initial cost of the IRV.

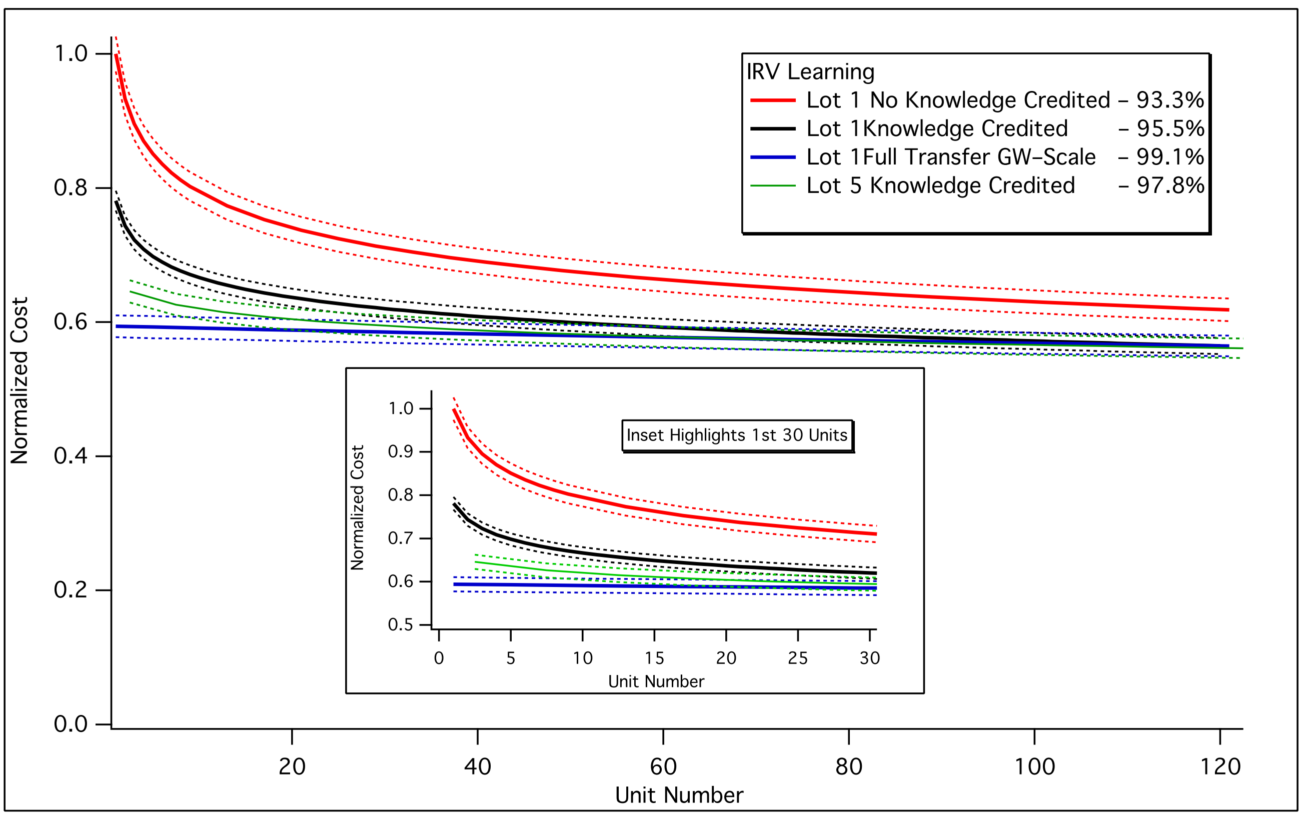

Figure 7–5: Learning Curve Comparing LEAD, the FOAK with Partial Knowledge Transfer, FOAK with Full Knowledge Transfer, and the FOAK with Partial Learning Transfer Produced in a Lot Size of 5 Units.

Components that are produced in small quantities should be the focus of significant advanced design effort. These small quantity production components such as the integrated pressure vessel can be major cost drivers of the IRV. Rapid learning is difficult to achieve in these components. Therefore, the initial design of these components must maximize the smartness of design. The smartness of design determines how easy it is to manufacture the component. It involves minimizing the amount of subtractive machining that must be performed, minimizing wasted material, and using automated manufacturing techniques. Addressing smartness of design is important for all of the IRV subcomponents. It is critical for the low volume components such as the integrated pressure vessel which is responsible for 45% of the cost of the IRV when produced in lots of 5.

Within the existing model, the following further refinements are suggested. The model of the generalized SMR IRV should be refined as more information becomes available about specific SMR designs. Using the existing model as a template, individual work elements can be expanded to include more detail, or refined to better reflect the realities of a nuclear manufacturing industry in a factory setting. Carrying the existing model forward would provide a tremendous head start towards more precise modeling or even to those wishing to model other possible SMR technologies (non-Light Water Reactor based systems).

Finally, the absolute manufacturing costs could be predicted using the methodology of this study. Absolute cost determination would require access to more detailed engineering drawings of the actual manufactured components. If this were pursued in the future, it would be best to replace some of the components that were simulated as labor with knowledge credited for actual invoiced purchased parts. This was not done in the initial work for two reasons, benchmarking the model and the investigation of learning.

D. Further Research Recommendations

i.) Model Development and Refinement

The parametric model detailed in Chapter 4 was developed as the foundation of an economic investigation into the cost structures of IRV manufacturing in the nascent SMR industry. This model was based on the generic model of an IRV using design specifications of the SMR industry in the United States[Welter, 2010][Westinghouse, 2011][Babcock &Willcox]. Thus the model is both simultaneously flexible and narrowly defined. The model is narrowly defined by the limitations imposed by the scope of this investigation, and the access to specific information. However, the model developed here is flexible because it is not limited to any particular SMR design.

The SEER modeling of the IRV is broken into work elements which amount to little more than the data sheets relating to the details of each fabrication process necessary to bring the individual IRV components from raw material to functional implementation. Each of these work elements is interchangeable and extremely versatile and customizable. This flexibility lends itself to modeling more than just the one generalized IRV design detailed already in the sections above. This model is valuable as a starting point for many other kinds of simulations featuring any number of SMR designs. The parameter space of the model is very large. This work just barely began investigations into the phase space of the available model. The model can be used to refine the design of SMRs, investigate the cost of money during the manufacturing process, refine the production time, etc.

One of the chief limitations of the simulations performed in this study is the extremely limited access to information, particularly, the specific design details of any of the main vendor designs. This limited the degree to which the generalized IRV design could home in on the particular phase space of any single vendor. Though the generalized design reflects an SMR IRV utilizing PWR technology, there are some instances where the complete lack of information introduces increased levels of uncertainty. For one example, one can look to the lack of information on even the basic nature of the control rod drive mechanism present in main U.S. SMR vendor designs. Being internal to the IRV, and therefore being exposed to the extreme operating conditions within the pressure vessel, the control rod drive mechanism may require significant design changes from the traditional control rod drive mechanisms present in existing, full scale GW reactors. Because there was no nonproprietary information available on these designs, the generalized design may not accurately represent what the SMR vendors will eventually utilize. As it stands, in either the LEAD, FOAK with knowledge credited, and the FOAK with full transfer of prior learning, the control rod drive mechanism represents only a small part of the overall cost of the IRV. However, if significant redesigns are required, and an entirely new technology is central to the new control rod drive mechanism, then the existing model will not accurately reflect the associated costs of novel technology.

However, if the model of the generalized SMR IRV is carried forward into a next generation of SMR economics research, the model can be refined to account for the design nuances of any SMR design. Using the existing model as a template, individual work elements can be expanded to include more detail, or refined to better reflect the realities of a nuclear manufacturing industry in a factory setting. Carrying the existing model forward would provide a tremendous head start towards more precise modeling or even to those wishing to model other possible SMR technologies. In fact, the model could be readily expanded to simulate non-PWR based small modular reactor designs.

ii.) Power Generation and Balance of Plant

To the end of developing a complete picture of SMR economics, the current generalized model must be extended to include the remainder of the SMR power plant structures. Included in the generalized IRV design are the reactor systems necessary for creating a source of usable energy using PWR technology. What remains of the power plant is the system of harnessing the steam produced by the IRV and generating electricity, and then there is the balance of plant (BOP).

First looking at the power generation, in many SMR designs each IRV is connected to its own steam turbine and electrical turbine generator [Westinghouse, 2011]. Together, these form the complete power generation system in an SMR power plant. Using the generalized IRV design described earlier, for a 1 GW plant using multiple SMRs, there would need to be ten IRVs and ten steam turbines and electrical turbine generators. Including the steam turbine and generator would change the proportion of materials, labor, and tooling in the final calculations of SMR production costs and learning rates. These components are highly complicated, and there are choices to be made concerning the production of these components which deserve a rigorous examination. For instance, the electrical generators could be treated as a purchased part, due to the availability of these components. Or, this component may be modeled using the techniques described above if a more specialized design was determined to be necessary. For the purposes of this report, it was necessary to leave these decisions, and ultimately, the production cost modeling and learning modeling of these components for future research efforts.

The BOP is the remainder of the facilities necessary to maintain operation of a power plant. In the case of an SMR power plant, the BOP includes: the structures that enclose the IRVs and power generation, the condensers for the steam, water treatment facilities, spent fuel containment pools, facilities related to the operation of the plant, etc. Various aspects of the BOP can be readily modeled using SEER. The construction processes central to determining the production cost of the BOP could be modeled using the techniques developed for IRV production. It does require that models for construction methods using concrete be integrated into the existing modeling paradigm.

This effort is further complicated by a number of other factors. Despite the emphasis on utilizing PWR technology, the central elements of SMR technology, namely the IRVs, necessitate changes to existing PWR BOP layouts and construction techniques. For instance, in the case of the NuScale SMR design [Welter, 2010], all of the IRVs are situated inside one very large containment pool, whereas the Westinghouse design makes use of large containment vessels for each of the IRVs [Westinghouse, 2011], which would be situated in its own concrete containment structure. Apart from the accommodations made for the IRV form factor, many SMRs have been designed in a world with a heightened awareness of terrorism and natural disasters [Campagna, 2010]. As a result, both vendors promise a litany of safety features including lower building profiles with many levels of underground facilities, etc. This represents only a small fraction of the issues raised when attempting to model the cost of the BOP. It is highly recommended that industrial engineering simulations be undertaken of all the BOP components to fully understand the economics of SMR manufacturing. These simulation tools are now readily available. The SMR industry would be wise to fully utilize these tools to improve manufacturing efficiencies prior to the production of SMRs.

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IX. Appendices

A. Investigation of Allied Industries

i. Aircraft Manufacturing

Aircraft manufacturing was the first industry to be recognized as following a learning curve model. T.P. Wright first established the use of power functions as the traditional modeling method for this and many other industries[Wright,1936]. Despite of the advent of newer, more sophisticated learning models, the Wright model is still the foundation of contemporary learning curve modeling efforts. The convention in the aircraft industry is to model the total labor hours as a function of unit number:

$$H = H_1 x^b \qquad \text{Eq. A-1}$$

Here H is defined at the total number of labor hours needed to complete x units. H_1 is the number of labor hours needed to complete the first unit, and b is the learning slope. The studies that were performed using this model ultimately agreed with the original estimate of 80%, as proposed by Wright. Later, Armen Archian [Archian, 1950] determined in his study of 22 different airplane models that the learning rate was dependent on the aircraft model [Benkard,2000]. His study explored the industry learning slope as a function of different aircraft models in production at the time. In doing so, he established the learning slopes for each of these models by manufacturer, and combined the individual results to determine an aircraft industry learning rate. However, despite the variance among the models, his combined data confirmed the traditional composite industry learning rate of 81% [Archian, 1950].

In recent years, researchers have paid special attention to the phenomenon of unlearning within the aircraft manufacturing industry [Cabral, 2001]. The implicit assumption at work in the standard learning models is that learning occurs continuously over the production lifetime of a model. However, when a manufacturing facility is not equally utilized over time or production moves between different models of aircraft, instances of unlearning are believed to occur. Such concerns were found to be relevant in vendor facilities which could accommodate production of multiple models while maintaining high production rates [Archian, 1950].

Aircraft manufacturing is a sophisticated process, involving many of the same operations at work in a potential SMR vendor factory. Airframes are pressure vessels that are cast and welded pieces of steel, titanium, and aluminum. These operations are carried out by large welding robots and teams of specially trained workers. An SMR vendor factory will almost certainly employ similar instrumentation. These airframes must be robust against stresses and strains produced by take off and landing, as well as pressure differentials while in flight. These characteristics are not unlike those of the IRV present in many SMR designs. Additionally, these specifications lead to extremely tight tolerances, employing expensive materials (Kevlar, graphite epoxy, titanium), as well as extensive testing. As a result, the production times for aircraft can be counted in the millions of labor hours [Asher 1956].

The similarities are not limited to manufacturing. In the realm of nuclear energy, the NRC plays an enormous role in regulating the licensing and operation of nuclear power stations [Goldberg,2011]. There is an analogous relationship at work between the aircraft industry and the FAA. The FAA regulations affect everything from what aircraft designs get approved, to how often planes must be serviced, even down to who gets to refuel a plane [FAA, retrieved 2013].

The aircraft industry analogy is limited by a few factors. Airplanes are considerably less materials intensive than SMR power generating stations. This translates to a greater sensitivity, both in cost and learning, to fluctuations in the cost of raw materials [Asher 1956]. The SMR industry has yet to mature to the point where any vendors have successfully produced a single functioning SMR power plant. As the concerns with production of multiple models are the concerns of a fully mature industry, they do not currently apply to the nascent SMR industry. Therefore, the effect of relearning will not be a major concern in SMR manufacturing for the near term [Asher, 1965].

ii. Shipbuilding

In the shipbuilding industry, it is commonplace to see the use of the Wright model[Wright 1936], when analyzing the cost reduction as a function of units produced. Traditionally, the cost is listed as labor hours per completed ship. There is consistent agreement on a learning rate of 80-85% for the ship building industry[Stump, 2012]. Cost analysis in the shipbuilding industry is categorized by ship structural elements. The hull, operational equipment, piping, and electrical work are all analyzed separately [Smallman, 2011].

With shipbuilding, there is a strong emphasis on the learning within labor intensive processes. Learning rates for specific manufacturing activities were investigated [Miroyannes 2006] due to the heavy reliance on skilled labor in fabrication, pre-assembly, and final assembly phases of construction. This investigation determined the learning rates, listed in Table 9–1, for four manufacturing processes frequently used in shipbuilding.

The shipbuilding industry has embraced modular construction and the general procedure of modular construction of large ships has been detailed[Defense 2012]. For large ships, steel plates are cut and welded in place to form the frames of modules. Depending on the size and shape, these units would undergo some final preparation before being joined together to form the hull of the ship. Other than the frames, much of a ship's internal structure is built inside these boxes in a module pre-assembly area. The modules could be outfitted to form all or part of storage spaces, machine rooms, control rooms, engine rooms, hall ways, or offices and housing. These modules are then assembled in sections which are joined to other sections forming the ship in a very linear process. The equipment necessary for

Manufacturing Activity	Learning Rate
Electronics	90-95%
Machining	90-95%
Electrical	75-85%
Welding	88-92%

Table 9–1: Learning Rates Typical of Shipbuilding Industry [Miroyannes, 2006].

assembling these sections can be very large and expensive, the most prominent being the dry-dock [Smallman, 2011]. These nonrecurring costs would be similar to those in the SMR industry, where similar production techniques would require large assembly areas equipped with high capacity cranes [Defense, 2012][Goldberg, S., 2011]. Recently, this modularization process allowed General Dynamics Electric Boat Division to deliver to the U.S. Military a Virginia class submarine a full year ahead of schedule [Defense 2012]. This process represents the ideal modular construction project, and it is precisely this model that the SMR industry hopes to mirror.

There are potential problems with making too direct a comparison between SMR manufacture and ship building. The shipbuilding industry does not have the regulatory oversight comparable to either the FAA or NRC. It is currently unclear how the ship building modular assembly process could cope with the added regulation without additional cost expenditures. It is recommend that as the SMR industry looks to shipbuilding to learn techniques that the focus be on nuclear submarine construction. Nuclear submarine construction has a regulatory environment and stakeholder engagement that is expected to be most similar to the SMR industry.

We have used the construction model utilized by the ship building industry to guide the breakdown of the reactor containment vessel. The similarities between naval reactors and SMRs as well as the use of modular construction techniques suggests that the pressure vessel of an SMR should have a learning curve similar to that observed in the shipbuilding industry.

iii. GW–Scale Nuclear Reactors

Learning curves used to model GW-scale reactor facilities were generally based on log linear, multiplicative regression models[Lester 1993]. These models come in many forms and are often augmented to suit the study. These functions usually take the form:

$$Y = Y_1 X^b \cdot A^{b_2} \cdot B^{b_3} \ldots \qquad \text{Eq. A-2}$$

where Y represents the total cost of producing X units, b_1 is the traditional learning slope, A and B represent some modulating quantities with b_2 and b_3 are exponents which determine the overall behavior. Taking the log of both sides produces the additive form most commonly seen in the literature [Lester 1993]:

$$\log Y = \log(Y_1) + b_1 \log(X) + b_2 \log(A) + b_3 \log(B) \ldots \qquad \text{Eq. A-3}$$

Generally, models of this kind are difficult to apply [Lester, 1993]. The advantage of these models is that they are suited for incorporating many variables into the cost estimation process. It should be noted that this methodology is based on historical data that is controversial [Goldberg. S., 2003].

The GW-scale nuclear reactor technology, currently in use, is the technological predecessor to the SMR industry. The U.S. Nuclear reactor fleet consists almost entirely of pressurized light-water reactors. The technology used in many SMR designs, including the designs put forward by Holtec, NuScale, Westinghouse, and Generation mPower [Welter, 2010][Westinghouse, 2011][Babcock & Wilcox, 2012, is based on PWR technology. The 100 MWe SMR design that served as a framework for this study has been based upon the technology currently being used in the GW-scale reactor industry. The component construction techniques were taken from those used in the construction of the modular Westinghouse AP1000..

iv. Semiconductor Industry

Modeling cost reduction in the semiconductor industry is a complicated task first attempted by Moore [Moore 1965]. The traditional learning curve models produce their most accurate results when modeling the behavior of one type of unit that is in constant production with no breaks in production to produce other types of unit. In the semiconductor industry this is a flawed model as multiple chip types are always in production and even multiple generations of the same chip can be in simultaneous production. For a full model of the learning curve for a semiconductor factory producing multiple chip types, with multiple generations of each chip in simultaneous production, a multiplicative regression model is necessary. However, over short enough time intervals, it is common to see the a traditional model, like the Crawford model, predict a short run learning rate of 80%[Irwin 1996]. Though this level of learning is considered to be higher than the rate for the industry as a whole [Nemet, 2012].

The integrated circuit fabrication industry is one of the most complex industries. The fabrication process requires hundred of steps performed in a clean room environment by automated machines [American Institute of Chemical Engineers, retrieved 2013]. The circuits are cut into silicon wafers in batches of 20-25 at a time. These wafers are both expensive ($1000-$10000), and fragile[Bohn 1995]. Each wafer holds a certain number of chips, depending on the chip type and generation. A production run begins with a certain number of chips. Production errors like particle contamination, breakage, or machine error, reduce the number of functioning chips per wafer. This introduces the idea of yield. The cost of producing a chip is the same if functions or if it does not. The production cost is therefore inversely proportional to the ratio of the number of chips on a wafer that function properly to the number that do not [Hatch 1998]. These losses can accrue very quickly, potentially losses of of up to 25%, which creates a very strong internal incentive to regulate production heavily [Bohn, 1995]. The use of automation and highly skilled labor in production, as well as the need to meet very rigorous standards of production, suggest that there are strong similarities between SMR and chip manufacture. Additionally, the use of harmful heavy metals and chemicals during production mirrors, in some part, the radioactive reactor core although in the opposite directions. It demonstrates the need to protect the manufactured part from the people as opposed to SMR manufacturing where the people are protected by the manufactured part [IAEA, 2007a].

The analogy of semiconductor manufacturing is missing a major regulatory body. Although, one could argue that the public serves as the regulatory body as a high failure rate does not bode well for consumer products [Loughmiller, retrieved 2012]. The production of multiple models as well as multiple generations of the same model at the same time within a factory nullifies the predictive capability of learning rates in the semiconductor industry. Additionally, the effect of losses in chip manufacturing has no obvious parallel in an SMR industry.

v. Photovoltaic Manufacturing

The photovoltaic (PV) industry commonly uses a traditional, log-linear learning curve based on cumulative cost as a function of output, in other words, the Wright model [Harmon, 2000]. A number of studies have been done to characterize the learning rate for the photovoltaic industry and have been summarized by Margolis [Margolis, 2002]. There are some good reasons for making using PV manufacturing as an analogy to the SMR industry. First, the photovoltaic industry operates similarly to the semiconductor industry in that the manufacturing process is extremely intensive. Second, the manufacturing facilities used by the industry are complex and often purchased from vendors [Bohn, 1995]. These manufacture construction devices are fabricated in a clean room environment using a combination of automated robots and highly skilled labor and are highly complex and greatly affect the learning in semiconductor processing[Yu, 2007]. Furthermore, they are themselves reasonable models for off-the-shelf parts for nuclear reactors.

Study	Learning Rate	# of obs	Years	Scope	Cost/Price Measure
Maycock and Wakefield (1975)	78%	16	1959-1974	US	PV module sale price
Williams and Terizan (1993)	81.6%	17	1976-1992	Global	Factory module price, based on Strategies Unlimited Data (from 1993)
Cody & Tiedje (1997)	78.0%	13	1976-1988	Global	Factory module price, based on Strategies Unlimited Data (from 1989)
Williams (1998)	82.0%	19	1976-1994	Global	PV module price
Maycock (1998)	68.0%	18	1979-1996	Global	PV module price, from text
Tsuchiya (2000)	83.3%	20	1979-1998	Japan	PV module government purchasing price, vs. Japanese cum. Production (sign. Fluctuation over time)
Harmon (2000)	79.8%	21	1968-1998	Global	PV module price, based on mix of sources (including Maycock, Ayres, NREL, Thomas, and Watanabe)
IEA (2000)	65%	11	1985-1995	EU	PV electricity costs (ECU.kWh), vs. Cum kWh Produced using a PV system (include BOS and shift from SHS to BIPV)
IEA (2000)	84% 53% 79%	9 4 10	1976-1984 1984-1987 1987-1996	EU	PV module price, based on EU-Atlas project data, vs global production.

Table 9–2: Learning Rate Differences in the PV Industry [Margolis, 2002].

Table 9–2 contains the data from nine studies which, surveyed over a wide range of years. The data shows a large variance in the learning rates within photovoltaic manufacturing. The range of learning rates presented by these studies covers almost all of the allowed values for the learning rate. Unfortunately, the observed variation in these learning rates makes it impossible to draw any direct conclusions to learning rates expected in SMR manufacturing from the values of learning curves in the photovoltaic industry.

vi. Wind Turbine Generators

Wind turbines are themselves, sophisticated pieces of technology built just at the limit of materials technology [Alonso, 2012]. The blades of the turbine are precision engineered to be light and strong; to be able to adjust their angle to best maximize wind exposure when wind speeds are low; to minimize wind exposure during high wind conditions; and each tower must have an internal temperature regulation system to maintain optimum operating temperatures. Wind farms can contain hundreds of these windmills, spread out over thousands of square miles. Producing these wind turbines takes thousands of tons of steel [Ancona, 2001]. Once they are made, they must travel to their final destination where they are assembled from the constituent parts. There are striking similarities between wind turbine generators and SMRs, both in manufacture, function, and transportation. The analogy is somewhat limited as the unit numbers are much larger for wind turbines than they would ever be for SMRs. This likely skews the unit cost in favor of the wind turbine generator industry. Also, the wind generation industry is not regulated to the extent that the SMR industry will be by the NRC.

The wind turbine manufacturing industry commonly makes use of the Wright [Wright, 1936] model in estimating cost reduction curves. Using the standard models, the learning rates have been measured to be in the range of 90-96% for the production and installation of wind turbines[NEEDS, 2006]. However, there is also data [Coulomb, 2006] which shows that there may be some dependance on power output, where a learning rate of 88% was observed. The lack of agreement is not a serious concern, as these values serve as a general indicator of the real learning curve. Based on this spread of values, the learning rate will fall somewhere in the range of 88-96%. These rates are very consistent with the predicted learning rate of the SMR IRV as detailed above.

vii. Food Service Industry

The typical tasks performed by any food service contractor are related to serving and replenishing food, setting and clearing tables, sanitizing facilities and equipment, preparing fresh fruits and vegetables prior to cooking, preparing all salads and beverages, serving prepared food items, handling foods, supplies, and equipment, maintaining the grounds of the assigned buildings, maintaining the food service equipment and quality-controlling the quality of the services provided [Reis, 1991]. All work must conform to pre-established standards of performance and is regulated by local health departments [U.S. Department of Health and Human Services]. Prior to starting work, contractor personnel receive instruction in the principles and practices of food services sanitation given by the base medical services personnel.

Learning rates in the food service industry are calculated using data from the contractor's production control reports and their reported cumulative average direct labor hours for the cumulative number of units produced from inception of the contract up to the end of each production control period. Reis, et al. [Reis, 1991], regressed the data against the log-transformed form of the learning curve model. Table 9–3 shows the learning percentages of ten start-ups in the food service industry are in the range of 85-98%. Reis [Reis 1991] observed a steady-state plateau occurring in the learning curve after 6 months of operation on the average. Thus, one cannot assume that the productivity improvement will continue indefinitely. However, this method can be applied to 'short-term and repetitive' tasks for smoothing the labor requirement of SMR assembly, especially on-site construction.

The differences mainly focus on the fabrication sequences or production sequence between these two industries. There are certain similarities between nuclear on-site construction work and the food industry. Because the limitation of work condition, it is difficult to use automatic robots as it is on the final construction site of an SMR. So, the on-site work is largely dependent upon manual labor, while the food service industry also has a significant manual labor component. Both industries perform repetitive work manual labor. Similar to the nuclear industries, food service also has strong regulatory requirements [U.S. Department of Health and Human Services]. Through they are different, all the workers must be managed to follow the regulations. In the food service industries, the quality of the food also must be controlled similar to SMR on-site work. This makes the food service industry a valid analog to SMR on-site construction.

Start-up Company	Measured Learning Rate
A	93.4%
B	87.8%
C	91.3%
D	93.3%
E	93.3%
F	95.8%
G	98.2%
H	92.2%
I	85.2%
J	84.8%

Table 9–3: Ten Service Start-Up Companies' Learning Rates

While most learning curves reflect not only learning from repetitive work but also technologies and scale; the nature of food service give us the pure learning curve that only reflects the relationship between the increasing productivity and the exercise of skills due to the lack of highly technical equipment used in food preparation. Considering the on-site work is also very labor-intensive, this is an effective means of predicting the mathematical slope of a new start-up, for both on-site manufacturing and service systems[Reis, 1991].

vii. Modular Construction

Though technically not an industry, modularization is one of the most important concepts used within the SMR industry. The general approach to modularization begins with a decomposition of a system into elements. Then, the interactions between the elements are identified and grouped according to the unique design specifications determined by the project goals. Modularization, in the context of nuclear energy, means that a large scale nuclear power plant can be broken down into separate modules with the goal of minimizing production costs [Smallman, 2011]. One of the largest modules in an SMR results from the collapse of the nuclear steam supply system into one transportable module, known as the integrated reactor vessel, IRV [Holtec, 2012]. The turbine generator is grouped with the IRVs as their own separate module. These modules can be assembled in a factory and shipped to the location of a future nuclear power plant. There, the modules are to be assembled minimizing the amount of on site work performed.

This study used as much modular construction as possible within a factory setting. The modularization approach has been central to the design process, though there are some limitations when considering the specifics of the SMR industry. Unfortunately, many of these were not within the scope of this work. However, they are important enough to mention here. One of the biggest improvements where modularization is expected to reduce manufacturing costs is in the Balance of Plant (BOP) including the on-site reactor buildings. These structures house the IRVs and turbine generators, as well as the spent fuel containment pool, water treatment, and offices. While many of these structures will be required to be robust concrete buildings, designed to resist security threats as well as nuclear and weather emergencies [Naus, retrieved 2012], other structures can be build as pre–assembled modules which are connected on–site. There appears to be no way to avoid on site construction of an SMR plant with current technology but the greater the number of pre–assembled modules used in final assembly; the greater the expected final assembly cost reduction. Modularization does appear to be reducing costs in the construction of the AP1000 and it is beginning to appear as if there is a learning curve (currently unquantifiable) in their construction. The first plants at the Vogtle site are running approximately $1B over budget[Southern 2012], while the second plants at SCANA's V. C. Summer plant are reported to be nearly $300M under budget due to lessons learned from Vogtle and China [Nuclear 2012]. It will be interesting to observe how learning in the modular AP1000 construction progresses.

B. Learning Curves

i. Learning

It has long been observed that, under most circumstances, manufacturing costs diminish over the production lifetime of a given product[Wright, 1936]. One of the more famous illustrations of this principle is "Moore's Law" from the semiconductor industry[Moore,1965]. Moore's Law is often stated in terms of the doubling of the number of components in an integrated circuit device. However, he described this doubling as being due to the reduction of the cost of each component on an integrated circuit chip, i.e. the learning curve of production. The phenomenon of learning curves was first properly identified and explained by Theodore Paul Wright, in 1936 in work based upon the nascent aircraft industry [Wright, 1936]. Originally, the reduction in cost was seen as a consequence of learning on the part of those responsible for construction and assembly[Gregory, 2006]. However, it has since been recognized that decisions made by management, technological improvements, and other efficiency gains lead to reduction in production costs as well [Gregory, 2006]. The use of learning curves is extensive in the field of cost estimation [Stump, 2012], and it is clear that learning curves can provide valuable insight into the viability of a prospective SMR industry.

There are two main descriptions of learning curves the Wright Model [Wright, 1936] and the Crawford Model [Lee, 1997]. Both the Wright and Crawford Models utilized learning curves based upon a power function. The main difference between the two is that the Wright Model determines a cumulative average cost of producing x units while the Crawford Model uses the marginal costs. Both models will be discussed in detail.

ii. Wright Model

Wright proposed that a power function governs the shape of a learning curve [Wright, 1936]. The power function took the form:

$$AC(x) = AC\, x^{b} \qquad \text{Eq. B-1}$$

where *AC* is the cumulative average cost of producing *x* units; *A* is a scaling factor which is related to the cost of the first unit; and *b* is the slope of learning curve. The exponent is referred to as the learning slope because graphically representing this function on a *log-log* scale yields a straight line, the slope of which is *b.*

It is important to clearly define the unit number *x*, the total cost of the first unit *A*, and the learning slope *b*. The unit number is simply the number of units to be put into production. The number of units is dictated by a number of complex and interrelated factors. The scaling factor, *A*, is often taken to be the initial cost of the first unit. This can be easily verified by using the number 1 to represent the first unit put into production, and substituting this in for *x*. The total cost of the first unit is crucial to estimating the learning curves. It is possible to derive a learning curve without a value for the total cost of the first unit, but, the resulting curve would provide no mechanism by which to compare differing learning scenarios. The learning slope contains all of the information about how much 'learning' is going on. To ascertain the value of *b*, a comparison between the lot average cost of producing some number of units *x,* and the lot average cost of producing twice that number *2x* is made. The ratio of the lot average costs:

$$\frac{TC(2x)}{TC(x)} = \frac{A(2x)^{b}}{Ax^{b}} = 2^{b} \qquad \text{Eq. B-2}$$

is solved for *b* by taking the *log* of both sides:

$$b = \frac{log(TC(2x)/TC(x))}{log 2} \qquad \text{Eq. B-3}$$

Therefore, *b* is the ratio of two logarithms. The argument of the logarithm in the numerator is what is sometimes called the learning rate. It is a number between 0.7 and 1 though there are no mathematical restrictions on this number, this range corresponds to cost reduction. When the cost of producing twice as many units does not decrease the average cost per unit, no 'learning' occurs and the ratio is equal to 1. A ratio of 0.7 corresponds to the highest levels of learning typically observed. When the cost of producing twice as many units increases the average cost, as sometimes happens, the ratio is greater than 1.This phenomenon is sometimes called “unlearning,”, or “negative learning,” and leads to an escalation in cost as the total lot size increases [Arnulf, 2010]. It also common to see this learning rate confused with the progress rate [Margolis 2002], which is simply one minus the learning ratio. The progress rate, therefore, has a range of 0 to 0.3 where 0 corresponds to no learning, and 0.3 corresponds to the highest rates of learning. All of these numbers are frequently expressed as percentages.

iii. Crawford Model

The Crawford model [Goldberg, S., 2003] has the form:

$$MC(x) = Tx^b \qquad \text{Eq. B-4}$$

This form is similar to the Wright model because they are both power functions, where the unit number and the learning slope are defined in the same way. The main difference is that in the place of the cumulative average cost, the dependent variable is marginal cost, and *T* is the total cost of the first unit. *T* is not actually the cost of the first unit when assuming a continuous probability density where *T* represents a constant which normalizes the continuous probability density function. For a detailed explanation, it is recommended that the reader look at "Statistical Methods for Learning Curves and Cost Analysis" by M. S. Goldberg and A. Touw [Goldberg, S., 2003].

Marginal cost (*MC*) is defined, mathematically, as the derivative of the total cost (*TC*) with respect to the unit number *x* , and the total cost is sometimes defined at the average cost per unit (*AC*) times the number of units (*X*) [Goldberg,2003].

$$MC(x) = \frac{dTC(x)}{dx}, TC = AC * X \qquad \text{Eq. B-5}$$

It is interesting to note that the Crawford model and the Wright model are equivalent under certain conditions. First, the unit number is taken to be a continuous variable. With a continuous unit number, integral calculus is used to approximate the incremental and cumulative cost. Also, it is assumed that the curves only consider the recurring costs. Recurring costs include: the cost of materials, labor, tooling, shipping, etc. Whereas, non-recurring costs are: costs to build the factory, research and development costs, licensing costs, etc. Under these circumstances, it can be shown that the Crawford model is equivalent to the Wright model by setting the two expressions for the total cost equal to each other.

$$TC = AC * X = \int_0^X MC(x)dx \qquad \text{Eq. B-6}$$

Next, the expression for the marginal cost according to the Crawford model is substituted

$$AC = \frac{1}{X}\int_0^X Tx^b dx \qquad \text{Eq. B-7}$$

and then integrated to give:

$$AC = \frac{1}{X}\left[\frac{TX^{b+1}}{b+1} + C\right] \qquad \text{Eq. B-8}$$

Simplification finally results in:

$$AC = \frac{TX^b}{b+1} + \frac{C}{X} \qquad \text{Eq. B-9}$$

The integration produces an integration constant which can be taken as the non-recurring costs and set equal to zero for the purposes of modeling the learning curve. Because the non-recurring costs are constant, and the goal is to examine the reduction in costs, it is safe to set these nonrecurring costs equal to zero which results in Eq. B-10:

$$AC = \frac{TX^b}{b+1} \qquad \text{Eq. B-10}$$

Next, the total cost in terms of the definition of the cumulative average cost proposed by Wright [Wright, 1936] is rewritten:

$$TC = AC * X = \left[AX^b\right] * X = AX^{b+1} \qquad \text{Eq. B-11}$$

Applying the equation for marginal costs results in:

$$MC = \frac{dTC}{dX}_{x=X} = \frac{d}{dx}AX^{b+1} = A(b+1)X^b \qquad \text{Eq. B-12}$$

A comparison of Eq. B-13 to Eq. B-4 with $T = A(b+1)$ shows that the Crawford and Wright models are equivalent. Based on the prevalence and direct applicability of the Wright model, it was the basis for the SMR learning curve analysis.

iv. Lot Mid–point Iteration

The approach to determining the learning curve for SMR production, using the models described above, is complicated. Because learning curves are used to fit existing sets of data, it is often the case that the data consists of lot sizes and total cumulative lot cost. Data sets of this kind are inherently discontinuous. The models detailed above rely on tying specific costs to specific unit numbers, as well as continuous distributions. In the absence of the ideal data set (continuous and direct unit to price correlation), a different approach must be utilized. To begin with, start with the definition of the Crawford model [Goldberg, S., 2003]

$$MC(x) = Tx^b \qquad \text{Eq. B-13}$$

and take the logarithm of both sides:

$$\log MC(x) = \log T + b \log x \qquad \text{Eq. B-14}$$

Despite being a linear function, which is amenable to an ordinary linear least squares fitting (OLS), the nature of the data prevents a direct application of OLS. The data consists of total lot costs and lot sizes, rather than individual costs per unit number. Using OLS to fit lots of data would produce a curve that would not be accurate to the underlying behavior. Instead, the lots are treated as distributions which have a typical unit which represents the whole lot. This is called the lot mid-point. The marginal cost in the equation above is therefore replaced with the lot average cost, *LAC,* and the unit number replaced with the lot mid-point *Q(b)*:

$$\log LAC = \log T + b \log Q(b) \qquad \text{Eq. B-15}$$

The definition of the *LAC* is given by:

$$LAC = \frac{TC_i - TC_{i-1}}{Q_i - Q_{i-1}} = \frac{T}{b+1} * \frac{(Q_i + 0.5)^{b+1} - (Q_{i-1} + 0.5)^{b+1}}{Q_i - Q_{i-1}} \qquad \text{Eq. B-16}$$

Using the definition of the average cost gives the definition of the lot mid-point:

$$LAC = T * \frac{(Q_i + 0.5)^{b+1} - (Q_{i-1} + 0.5)^{b+1}}{(b+1)(Q_i - Q_{i-1})} \qquad \text{Eq. B-17}$$

with

$$Q(b) = \left[\frac{(Q_i + 0.5)^{b+1} - (Q_{i-1} + 0.5)^{b+1}}{(b+1)(Q_i - Q_{i-1})}\right]^{\frac{1}{b}} \qquad \text{Eq. B-18}$$

In this notation, Q_i represents the Q^{th} unit in the i^{th} lot. Therefore, the first unit in the i^{th} lot is $Q_{i-1}+1$. The addition of 0.5 in the numerator is to offset this counting convention. Considering the purpose of this process is to determine the learning curve which best fits the data, these results do not seem promising as it appears that to determine the learning slope it one needs to know the learning slope in advance. This is not an actual problem. All that is necessary is to choose a value for *b* to use to minimize the sum-of-squared errors between the right-hand predictor and the actual values of the logarithmic lot average cost:

$$= \sum \left[\log LAC_i - \log T - b \log Q(b)_i\right]^2 \qquad \text{Eq. B-19}$$

Though quite cumbersome, lot mid-point iteration is a robust and reliable method for determining the learning slope, and thereby the learning curve, while simultaneously minimizing the error in the curve. The chief concern is arriving at the curve quickly. Without a general idea of the value for *b,* this becomes a frustrating guessing game. To avoid this, it is necessary to estimate the value of *b* in advance.

C. Simplified View of IRV Model

Figures 9–1 and 9–2 show a flow chart representative of the manufacturing breakdown of the IRV within the simulation. It is not meant to represent a full break down of the model IRV but it clearly defines the major focal points of the simulation.

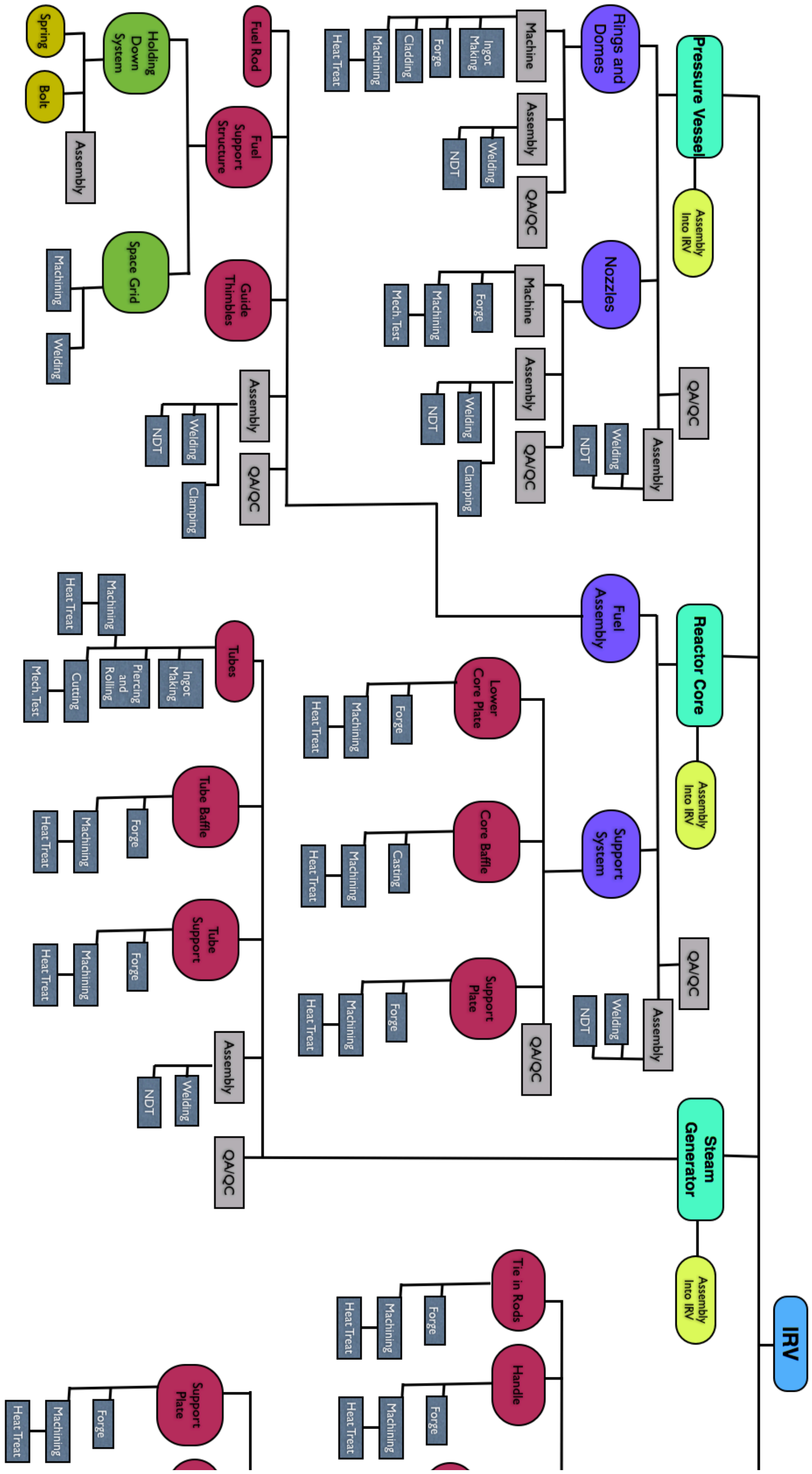

Figure 9–1: Flow Chart of the Model Showing the Breakdown of the Generic IRV Design into the Simulation Components (Part A)

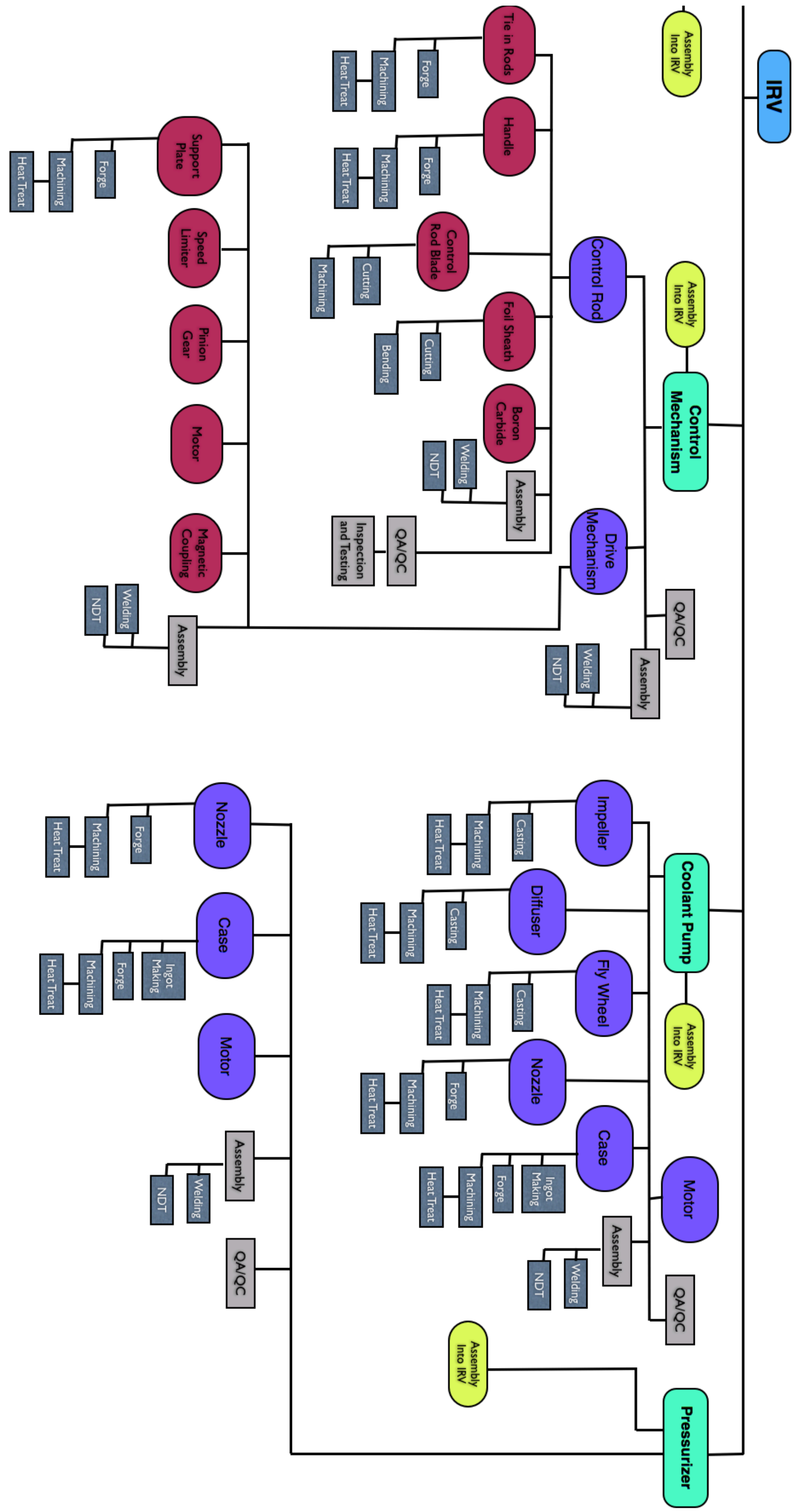

Figure 9–2: Flow Chart of the Model Showing the Breakdown of the Generic IRV Design into the Simulation Components (Part B)