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A Foundational Methodology For Determining System Static Complexity Using Notional Lunar Oxygen Production Processes

Nicholas J. Long

A FOUNDATIONAL METHODOLOGY FOR DETERMINING SYSTEM STATIC COMPLEXITY USING NOTIONAL LUNAR OXYGEN PRODUCTION PROCESSES

by

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This thesis, submitted by Nicholas James Long in partial fulfillment of the requirements for the Degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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Dean of the School of Graduate Studies

april 24, 2014

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Nicholas James Long
April 24, 2014

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ABSTRACT

This thesis serves to develop a preliminary foundational methodology for evaluating the static complexity of future lunar oxygen production systems when extensive information is not yet available about the various systems under consideration. Evaluating static complexity, as part of a overall system complexity analysis, is an important consideration in ultimately selecting a process to be used in a lunar base. When system complexity is higher, there is generally an overall increase in risk which could impact the safety of astronauts and the economic performance of the mission. To evaluate static complexity in lunar oxygen production, static complexity is simplified and defined into its essential components. First, three essential dimensions of static complexity are investigated, including interconnective complexity, strength of connections, and complexity in variety. Then a set of methods is developed upon which to separately evaluate each dimension. Q-connectivity analysis is proposed as a means to evaluate interconnective complexity and strength of connections. The law of requisite variety originating from cybernetic theory is suggested to interpret complexity in variety. Secondly, a means to aggregate the results of each analysis is proposed to create holistic measurement for static complexity using the Single Multi-Attribute Ranking Technique (SMART). Each method of static complexity analysis and the aggregation technique is demonstrated using notional data for four lunar oxygen production processes.

CHAPTER I

INTRODUCTION AND BACKGROUND

I.1 Introduction to ISRU and High-Level Decision Making

Human space exploration of the solar system has been limited to orbital flights and brief expeditions on the lunar surface. Cost and technological capability are significant barriers that limit the potential of human space exploration. Since the Apollo era, exploration of Mars has been one of the most desired goals of space exploration. In order for a Mars mission or longer duration lunar mission more to be economically and technically feasible, the resources that exist on the surface must be utilized. In space exploration, the utilization of resources found on another celestial object for the greater good of an objective is referred to as In Situ Resource Utilization (ISRU). One of the various potential forms of ISRU that could be performed on the Moon or Mars is extracting oxygen from regolith or ice. The extracted oxygen could then be utilized for life support and the in-space manufacturing of liquid oxygen and liquid hydrogen (LOX and LH2) propellant.

ISRU has the potential to make more difficult space exploration come to fruition, but ISRU has never been functionally tested in space. Before executing ISRU, testing and learning to optimize ISRU techniques on the Moon is a starting point for more difficult mission scenarios, such as a Mars mission. The Moon serves as an excellent test bed for the beginning of this technological endeavor. The Moon is significantly closer to the Earth than Mars, which means that if problems occur, assistance can be sent to the lunar surface within a timescale of a few days rather than the several months required to reach Mars. There are distinct similarities in the processes that could be utilized to extract oxygen on Mars to that on the Moon. For example, most of these processes feature a primary chemical reaction that occurs in some form of a reactor chamber. Many processes then use electrolysis to isolate the oxygen from the water which is a byproduct of the chemical reaction. However, there are many distinct differences, such as the use of different oxygen sources and acceptable ore grade of the oxygen sources. Using the Moon as a test bed would allow for the optimization of resource extraction and utilization and better prepare the technology for more difficult planetary exploration endeavors, such as Mars exploration.

Often, high-level managers face the situation of having to make decisions early in a program or project, but a non-ideal amount of information is available. An educated decision must be made in spite of the present disadvantage. “Good” decisions can still be made by utilizing the current knowledge that is accessible about the systems and making educated predictions of future conditions. This decision scenario is currently the case with lunar oxygen production. Eventually, a space agency will have the capacity to develop a long-term lunar settlement, but before this can occur, decisions must be made about the technical requirements of the mission under informational uncertainty.

There are numerous factors that ultimately play a role in the eventual selection of one lunar oxygen production process, which partially include: feedstock requirements, power requirements, materials requirements, system complexity considerations, lunar base layout optimization, lunar base risk reduction, and cost performance (all of these factors are further defined below). System complexity is an important decision-making consideration because an understanding of system complexity allows for informed management decisions about design choices or the distribution of resources based on reasoning (Fang & Marle, 2013). However, it is not evident that much consideration has been given to system complexity in the literature surrounding lunar oxygen production. When a specific lunar oxygen process must be selected, all of these factors must be deeply studied to make an educated decision about what the ideal lunar oxygen production process is and how it should be implemented. Table 1 identifies the essential considerations for the selection of a lunar oxygen production process.

Table 1. List of Various Essential Considerations for the Selection of a Lunar Oxygen Production Process.

Feedstock Requirements: How much ore is required to extract a unit of oxygen? A less efficient process of producing oxygen will require more ore to be extracted and processed. The metric for measuring feedstock requirements is kilograms.

Ore Grade: What quality of ore is needed to yield a desired output of oxygen? Ore grade is characterized by the composition of the ore and how easily oxygen can be extracted. In regolith ore, when higher concentrations of oxide-bearing minerals exist (particularly ilmenite), more oxygen can be extracted. In permafrost ore, higher concentrations of water will yield more extractable oxygen. Further, ore grade is negatively influenced by contaminates which reduce oxygen yield and/or damage the processing equipment.

Power Requirements: Individual components of processes require various amounts of electrical power and, if a specific process requires a substantially greater amount of power, a larger infrastructure will need to be set up for power generation and collection. The metric for measuring power requirements is watts.

Material Requirement: Material requirement is the mass of all equipment in the oxygen production system, excluding the feedstock. Equipment components of specific processes require different materials with different weights. Certain processing equipment requires more material than used on other processes. The metric for measuring materials requirements is kilograms.

System Complexity: With increasing components, processing steps, control mechanisms, and technological immaturity associated with a process, the overall system complexity increases. Additionally, with increasing complexity is increased risk. This thesis develops a set of metrics that can be used to evaluate a system's static complexity, an important part of the larger holistic concept of system complexity.

Lunar Base Layout Optimization: Optimization of the placement of lunar base components will be necessary to maximize the efficiency of production and safety of the astronauts, while minimizing system cost and energy usage.

Lunar Base Risk Reduction: Implementation of various measures to reduce risk to astronauts working on a lunar base will be a vital consideration in the selection and design of a lunar oxygen production process.

Cost Performance: Implementing various measures to reduce total cost of the lunar base mission and selecting equipment that minimizes cost will benefit the financial feasibility of the mission.

I.2 Lunar Resources and Lunar Oxygen Production

There are two potential sources of oxygen on the lunar surface. The lunar surface consists of 40 to 50 percent oxygen as oxide-bearing minerals. The major oxygen-bearing minerals that exist on the Moon's surface are ilmenite, pyroxene, anorthite, and olivine (Zhao & Shadman, 2007 and Dr. Mike Gaffey, personal communication, April 25, 2014). Oxygen is also contained in permafrost (ice), which exists in permanently-shaded regions of the lunar poles (Colaprete et al., 2010). More than 20 different processes for lunar oxygen extraction and retrieval have been proposed, and there is a subset of these processes that are considered to be more feasible from an economic and technological prospective (Taylor & Carrier, 1993). The lunar oxygen production processes that have received the most attention in the literature are: hydrogen reduction of ilmenite, carbothermal reduction, and molten silicate electrolysis. And more recently, the possibility of extracting oxygen from polar lunar permafrost using microwaves has been considered.[1] However, none of the available processes have been extensively studied to the same level as a terrestrial industrial chemical process. Thus, only mostly notional systems have been proposed and studied with the exception of some laboratory and terrestrial feasibility testing.

I.3 System Complexity and Static Complexity

The intent of this research is to focus on the single concept of static complexity, which is an important constituent of the larger concept of system complexity. Static complexity is defined as the complexity associated with the linkages, interconnections, and components of a process, i.e., its steady state topology (Casti, 1979, 98).[2] The overall total complexity of the system considers every dimension of complexity, which largely includes static and dynamic complexity.[3] The concepts of system complexity and, furthermore, static complexity, have been studied in a variety of applications,

[1] See section III.1.2 for more information on these processes.
[2] See sections III.2 and VI.1 for further details about static complexity.
[3] See section III.2 for more details on static and dynamic complexity.

which includes engineering applications. There is significant work in the literature regarding the concepts of system and static complexity, and a summary of these concepts is described in section III.2. However, the literature on system complexity has made the assumption that an optimal amount of information is available about each alternative system or process to complete the analysis of the complexity of a system. Lunar oxygen production is still in an early phase of research where only suboptimal information is currently available. Thus, this thesis is focused on developing the foundational framework for static complexity analysis, which sets a baseline for a more complete analysis when lunar oxygen production processes are no longer notional systems.

CHAPTER II

PROBLEM STATEMENT AND GOALS

II.1 Problem Statement

This thesis serves to develop the foundational framework for static complexity analysis in lunar oxygen production systems, which sets a baseline for a more complete analysis when lunar oxygen production processes are no longer notional systems.

II.2 Goals

The goals of this analysis are the following:

1. Investigate how static complexity has been developed in the literature from a generic perspective and how it has been defined for engineering applications, specifically industrial chemical processes.

2. Identify the various dimensions which contribute to the overall static complexity for an industrial chemical system and determine which are essential to evaluate and which can be studied.

3. Using the pre-existing knowledge of static complexity, develop a set of methods upon which to evaluate each separate dimension of static complexity in the setting of lunar oxygen production systems. Each dimension of static complexity is evaluated separately, providing several levels of transparency about a system's static complexity. The analysis must consider the differences between terrestrial and lunar industrial chemical systems.

4. Demonstrate the developed metrics by application to notional lunar oxygen production processes.

5. Provide explanation for how one might interpret various types of data provided by the analysis.

CHAPTER III

LITERATURE REVIEW

III.1 Review of Lunar Oxygen Production and Various Proposed Processes

III.1.1 Brief History of Lunar Oxygen Production

In the 1960s, space scientists realized that the settling of an autonomous colony on the Moon would realize tremendous cost savings if oxygen were manufactured by in situ production. One of the first original pioneering works of lunar oxygen production is Rosenberg et al. (1966), which details the possibility of using chemistry similar to that of steelmaking (carbothermal reduction) to extract oxygen from the surface regolith. Following several years of conceptual development, works such as Christiansen et al. (1998) who authored an Eagle Engineering Report to NASA, detailing more of the technical intricacies of lunar oxygen production that were largely missing in earlier conceptual development.

More recent ideas about lunar oxygen production are based on using polar permafrost (ice) on the Moon to extract oxygen. In the early 2000s, water in the form of permafrost was confirmed to exist in the permanently-shaded polar regions of the Moon (Colaprete et al., 2010). Recent literature suggests an increased interest in oxygen extraction through polar permafrost and the possibility that it might be a highly viable option. However, a further understanding of the characteristics of the polar ice is necessary to assess its potential as a viable method (Eldridge & Kaukler, 2009).

To date, more than twenty processes have been proposed for extracting oxygen on the Moon, and each has gone through various degrees of development. These processes can be grouped into five basic categories: (1) Solid Gas Interaction, (2) Silicate/Oxide Melt, (3) Pyrolysis, (4) Aqueous

Solutions, and (5) Co-Product Recovery. A list of these processes, which is derived and expanded upon from the list provided in Taylor and Carrier (1993, 72), and their respective literature references is provided in Table 2 below.

Table 2. List of Potential Processes for Extracting Oxygen on the Moon.

Processes	References
Solid Gas Interaction	
Ilmenite reduction with hydrogen with hydrogen	Gibson and Knudsen (1988)
Ilmenite reduction with C/CO	Chang (1959); Zhao and Shadman (1990)
Ilmenite reduction with methane	Friedlander(1985)
Glass reduction with hydrogen	McKay et al. (1991)
Reduction with hydrogen sulfide	Dalton and Hohman (1972)
Extraction with fluorine	Burt (1988); Seboldt et al. (1991)
Carbochlorination	Lynch (1989)
Silicate/Oxide Melt	
Molten silicate electrolysis	Haskin (1985); Colson and Haskin (1990)
Fluxed molten silicate electrolysis	Keller (1986); Keller and Tabernaux (1991)
Caustic dissolution and electrolysis	Dalton and Hohman (1972)
Carbothermal reduction	Rosenberg et al. (1966); Cutler and Krag (1985)
Reduction with hydrogen sulfide	Dalton and Hohman (1972)
Magma partial oxidation	Waldron (1989)
Li or Na reduction of ilmenite	Semkow and Sammells (1987)

Table 2 cont.

Processes	References
Pyrolysis	
Vapor phase reduction	Steuer and Nerad (1983)
Ion (plasma) separation	Steurer and (Nerad) (1983)
Plasma reduction of ilmenite	Allen, et al. (1988)
Microwave extraction of polar permafrost	Eldridge & Kaukler (2009)
Thermal extraction of polar permafrost using solar power	Frias, et al. (2012)
Aqueous Solutions	
HF acid dissolution	Waldron (1985)
H_2SO_4 acid dissolution	Sillivan (1990)
Co-Product Recovery	
Hydrogen/helium water production	Christiansen et al. (1988)

For processes that utilize lunar regolith, hydrogen reduction of ilmenite is the most extensively tested and studied process. Various forms of reduction of ilmenite have gone through laboratory testing, featuring reduction agents such as carbon, hydrogen, and methane using different types of reactor beds, e.g., rotating, fluidized, etc. (Zhao & Shadman, 1993). Carbothermal reduction and molten silicate electrolysis have also been tested in a laboratory setting, confirming their potential as viable methods (Gustafson et al., 2010 and Sibille & Dominguez, 2012). For extraction of oxygen from polar permafrost, microwave extraction has seen the most development, with a NASA test confirming its potential as a viable method (Ethridge & Kaukler, 2009). Hydrogen reduction of ilmenite and carbothermal reduction have been tested in a "lunar like" environment on a Mauna Kea, Hawaii test site (Clark, 2009). Each experiment successfully mined lunar tephra (regolith analog) and produced oxygen successfully.

III.1.2 Four Primary Lunar Oxygen Production Processes

Consolidated information is presented about the four major lunar oxygen production process that have been studied over the last several decades. The discussion includes essential information, diagrams, and advantages and disadvantages for each process that are identified in the literature.

III.1.2.1 Hydrogen reduction of ilmenite. Hydrogen reduction of ilmenite utilizes a two-step chemical process, as follows:

$$FeTiO_3 + H_2 \leftrightarrow Fe + TiO_2 + H_2O \qquad (1)$$
$$H_2O \leftrightarrow H_2 + 1/2O_2 \qquad (2)$$

First, either pre-beneficiated ilmenite (FeTiO3) or lunar regolith containing ilmenite is forced into a chemical reaction with hydrogen in a reactor bed. The reactor could be fluidized, rotating, or some other configuration. For the reaction to occur, temperatures must reach 700–1000°C. Water is a product of the reaction and can be further converted into oxygen and hydrogen via electrolysis. The oxygen and hydrogen can be separately stored. Additionally, the hydrogen can be reused for further processing (Taylor & Carrier, 1993, 73-75). The process using a fluidized-bed reactor is shown in Figure 1.

Hydrogen reduction of ilmenite has been performed successfully in a laboratory environment. Lockheed Martin and NASA produced the pilot plant which successfully demonstrated the feasibility of the process. The pilot plant, a photograph of which is shown in Figure 2, was tested in the terrestrial setting of Mauna Kea, Hawaii using tephra soil as a regolith simulant. Tephra soil has a similar texture to that of lunar regolith. Hydrogen reduction of ilmenite has also been tested in a laboratory setting using NASA JSC-1A regolith, which better represents the actual composition of lunar regolith than the tephra simulant (Clark, 2009).

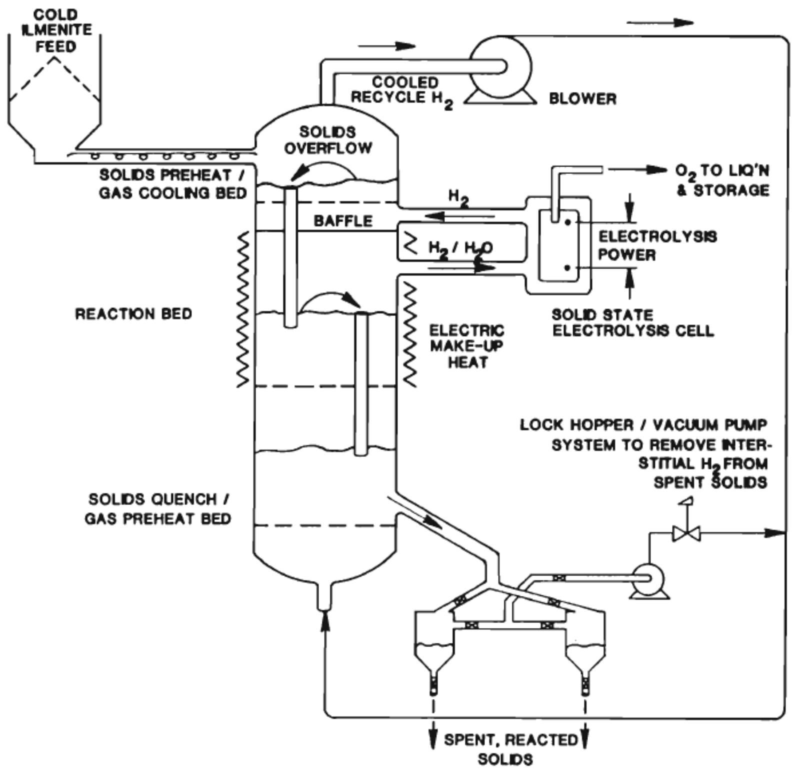

Figure 1. Continuous fluidized-bed process for ilmenite reduction by hydrogen for the production of LLOX, modified after Gibson and Knudson (1988).

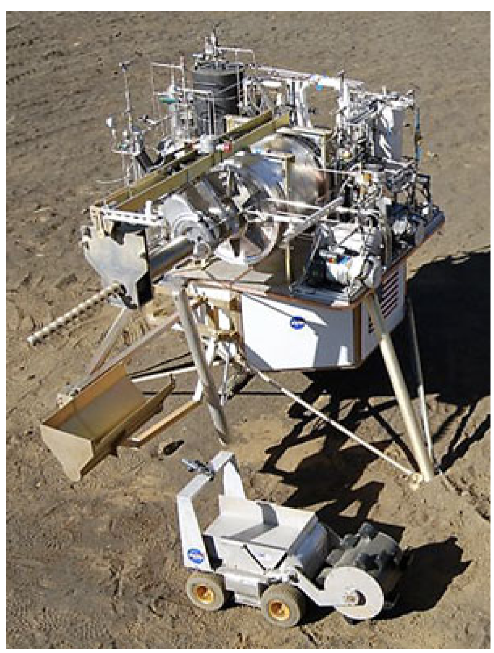

Figure 2. NASA/Lockheed Martin Pilot Plant.

The advantages and disadvantages of ilmenite reduction to produce oxygen are listed below (Taylor & Carrier, 1993, 73-75):

Advantages

- Ilmenite can be readily beneficiated from lunar mare and basalt.
- Kinetics of the ilmenite reduction are more rapid than from other silicate minerals.
- Chemical process exhibits a comparatively low reaction temperature easing the thermal stress on the reactor lining.
- Process has undergone the most extensive testing yet of any process.
- Chemistry of the process is relatively straight forward and uncomplicated.

Disadvantages

- Lunar ilmenite contains chemical impurities which are byproducts of the chemistry of the process: Mg (up to 8% MgO) and Cr (up to 2.5% Cr_2O_3).
- Additionally, the sulfide mineral trolite (FeS) that commonly exists in mare soils is corrosive to the reactor chamber. The presence of this contaminate necessitates its removal from the reactor chamber, ultimately requiring more processing equipment. The removal procedure is not seen to be of significant difficulty (Dr. Mike Gaffey, personal communication, April 27, 2014)
- Dependence on external source of hydrogen gas a reactant and would need to be brought up from Earth.
- For reasonably efficient production of oxygen, ilmenite must be beneficiated requiring more processing equipment.
- The process produces a low pass per conversion of H_2O to O_2, which results in an increased gas flow rate and a need for larger reactor equipment and increased mass.

III.1.2.2 Carbothermal reduction. Carbothermal processing utilizes chemistry from steelmaking and coal-gas forming with electrolysis to yield oxygen. Experiments performed on the reduction of molten silicates by methane required temperatures of 1600°C and followed the below chemistry.

$$Mg_2SiO_4 + 2CH_4 \leftrightarrow 2MgO + Si + 4H_2 + 2CO \tag{3}$$
$$CO + 3H_2 \leftrightarrow CH_4 + H_2O \tag{4}$$
$$H_2O \leftrightarrow H_2 + 1/2O_2 \tag{5}$$

The process involves three steps: ilmenite smelting, iron decarburization, and hydrocarbon reforming, as shown in Figure 3. The water is then electrolyzed to yield oxygen and hydrogen for separate storage (Taylor & Carrier, 1993, 88-90).

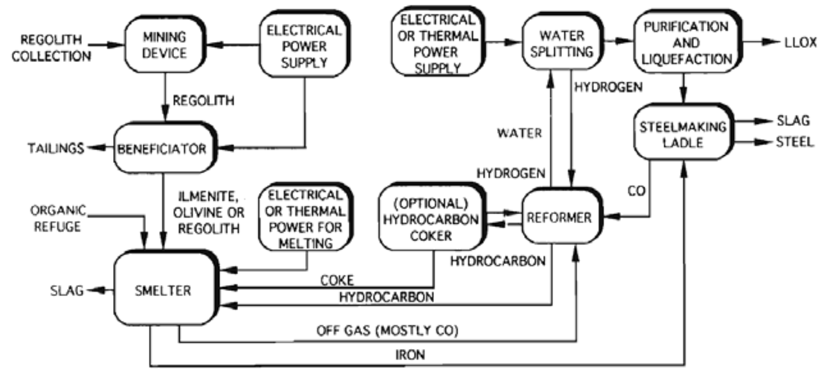

Figure 3. Flow Diagram for the production of LLOX by the carbothermal reduction process, modified after Cutler and Krag (1985).

Figure 4 shows a diagram of the experimental device used in the experiment.

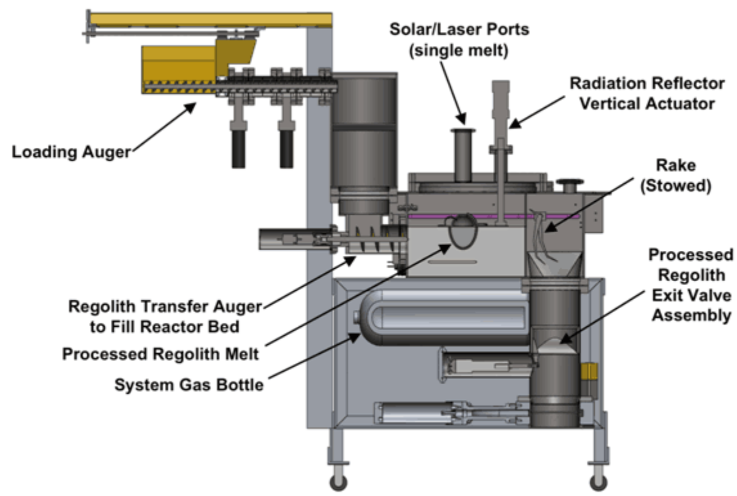

Figure 4. Schematic of Orbitec Integrated Carbothermal Reduction of Regolith System (Gustafson, et al., 2010).

The advantages and disadvantages of carbothermal reduction of regolith to produce oxygen are listed below:

Advantages

- Process is flexible in that it can theoretically operate with a variety of lunar feedstock compositions, although it will run best on simple oxide melts (Taylor & Carrier, 1993, 88-90).
- Process should theoretically yield more oxygen than many other processes. At the high temperatures required for processing, carbon extracts 1.33 times its mass in oxygen,

whereas only 0.56 to 0.84 times its mass is extracted at temperatures that are required for hydrogen reduction of ilmenite (Christiansen et al., 1988, 8-9).

- Less material will be mined in comparison to hydrogen reduction of ilmenite (Christiansen et al., 1988, 8).
- Close terrestrial analogues exists for carbothermal reduction: smelters, steelmaking, and hydrocarbon forming (Christiansen et al., 1988, 8).

Disadvantages

- Process is exceedingly complicated, potentially rendering it unfeasible (Christiansen et al., 1988, 8).
- Reactor requires a very high temperature (≈1600º C) (Taylor & Carrier, 1993, 88-90). This temperature requires considerable input energy and ilmenite, or other oxides, must be processed in a molten state, which subjects the reactor to very high temperatures. Molten silicates and metal are highly corrosive, likely limiting the life of processing equipment and warranting the eventual replacement of the inside refractory lining (Stump et al. 1988).
- Requires an external source of carbon as a reactant.
- Reductant makeup from Earth may be substantial, i.e., 5–20 percent of the carbon (Taylor & Carrier, 1993, 88-90).
- Because steel is a byproduct in the process, additional quality assurance is required to generate quality structural forms (Christiansen et al., 1988, 9).
- Recovery of the carbonaceous reductant in the slag and metal phases would require more equipment and weight and must be compared to importing the carbon from Earth. (Christiansen et al., 1988, 9).

III.1.2.3 Molten silicate electrolysis. Molten silicate electrolysis is conceptually simple. The chemistry of the process is shown below:

$$4\,(SiO^{-}) \leftrightarrow 2(Si\text{-}O\text{-}Si) + O_2 + 4e^{-} \qquad (6)$$

Like carbothermal reduction, a feedstock abundant in silicate minerals (such as anorthite, olivine, and pyroxene) is placed into the electrolysis chamber. Two electrodes are placed into the molten feedstock and a current is created between the two electrodes, which sustains a temperature of 1300–1700°C in the reaction vessel, as depicted in Figure 5. In this process, oxygen is generated at the anode (anode reaction shown below), and metals such as Fe and Si are generated at the cathode, which exits the process as slag (Taylor & Carrier, 1993, 81-84).

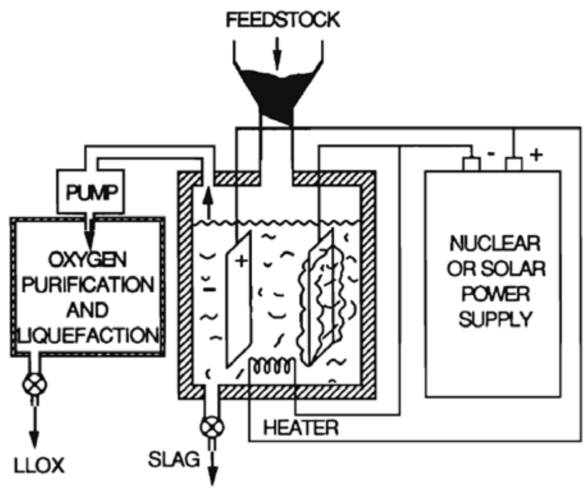

Figure 5. Schematic Diagram of the Electrolysis of Molten Silicate Depicting the Production of Oxygen at the Anode and Various Metals at the Cathode (Taylor & Carrier, 1993, 82).

A photograph of a laboratory-scale molten silicate electrolysis reactor is shown in Figure 6.

Figure 6. Molten Silicate Electrolysis Reactor in Laboratory Operation (Sibille & Dominguez, 2012).

The advantages and disadvantages of molten silicate electrolysis to produce oxygen are listed below:

<u>Advantages</u>

- By comparison to other lunar oxygen production processes, the number of processing steps is lower (Taylor & Carrier, 1993, 81-84).
- Process can function with a wide variety of feedstock compositions (Taylor & Carrier, 1993, 81-84).

- Energy requirements have been determined to be less than that of other processes (Colson & Haskin, 1990).
- No mass penalties from transporting reactants from Earth, such as with carbothermal production or hydrogen reduction of ilmenite (Taylor & Carrier, 1993, 81-84).

Disadvantages

- There is limited industrial experience with high temperature silicate melts (Taylor & Carrier, 1993, 81-84).
- The temperatures required for efficient processing are 1300 to 1700ºC, which is anticipated to cause corrosion of the reactor lining and the electrodes placed in the cell (Taylor & Carrier, 1993, 81-84).
- If oxygen is produced for propellant use, no H_2 is derived from the reaction. Thus, H_2 would need to be brought up from Earth or produced by another means.

III.1.2.4 Extraction of polar permafrost. Microwave extraction of polar lunar permafrost involves using single or multiple 2.5Ghz microwave generators to penetrate and heat polar ice in a pressure sealed chamber. The permafrost rests on the lunar surface at cryogenic temperatures. The water sublimes and can be captured as water vapor via a cold trap. The water is then electrolyzed to yield oxygen and hydrogen, which are then separately stored. The difficulty associated with capturing freed water in a cold trap in the lunar setting is not yet known (Ethridge & Kaukler, 2009).

The chemistry of the process is shown below (same as electrolysis for hydrogen reduction of ilmenite and carbothermal reduction):

$$H_2O \leftrightarrow H_2 + \frac{1}{2}O_2 \tag{7}$$

Photographs of laboratory-scale equipment for microwave extraction of moondust (regolith simulant permafrost) are shown in Figure 7.

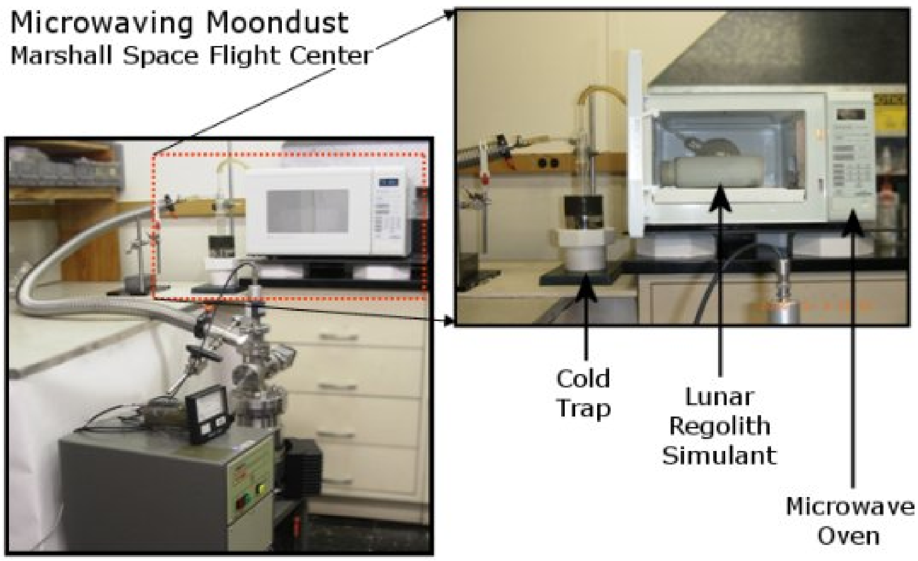

Figure 7. NASA MSFC Feasibility Demonstration of Microwave Extraction of Polar Permafrost.

Not much is known about the problems associated with this process because a great deal of polar ice compositional characterization still needs to be performed and the process itself needs significant further development. The known advantages and disadvantages are listed below.

<u>Advantages</u>

- Microwave extraction could potentially greatly minimize the need for excavation of ice.
- Microwave heating has an advantage over furnace or solar-concentrated heat because the microwaves penetrate deeply into the ice.
- Laboratory observations have demonstrated that lunar regolith couples well with the typical frequency range (1–10 GHz) of most commercially available magnetrons.
- Lunar polar water is likely to exist in high concentrations (5.6 +/- 2.9 percent), as indicated by the LCROSS mission.

Colaprete (2010)

<u>Disadvantages</u>

- All ice extraction equipment must be able to function at lunar polar temperatures (40–100°K). Also, the polar regions can experience extreme temperature changes from 40–270°K. The equipment must be able to handle the temperature stress from extreme temperature changes (Eldridge & Kaulkler, 2007).
- Lunar ice is likely to be highly compacted. Microwave energy may not be able to penetrate deeply into the ice, limiting effectiveness of the process (Eldridge & Kaulkler, 2007).

- Solar array will have to rotate with lunar day and when the sun's angle is low in polar locations (Duke, 1998).

III.2 Review of System Complexity

III.2.1 Review of Complexity and System Complexity

The literature suggests that complexity is a "fuzzy" and subjective concept that has proven to be difficult to define. Any definition of complexity itself is subjective in nature, i.e., "…[T]he perception of the complexity of a system depends on the context of the study and the degree of detail to which the thing is viewed… ." (Wall , 2009). Complexity is difficult to analyze quantitatively, and when such an analysis is performed several assumptions must be stated. In defining complexity, Fang and Marle (2013, 1) state that "...[t]he existence of numerous and diverse elements which are strongly interrelated is one of the main characteristics of complexity... ." Fang and Marle (2013, 2) also state that "... the complexity of a project leads to the existence of a network of interdependent risks." However, as these authors indicate, a more precise definition of complexity is dependent upon the context of the study.

Several authors have developed generic theories about complexity or "system complexity" analysis. Others have developed methodologies describing how to model the complexity of computer codes, various ecological processes, or other specific systems. All described methodologies for evaluating complexity are contingent on the context of the system and how complexity is framed. There are two overarching approaches in which the literature generally views the concept of complexity. There is the North American approach which emphasizes the spontaneous coevolution of entities (agents) in a complex system. "Agents restructure themselves continuously, leading to new forms of emergent order consisting of patterns of evolved agent attributes and hierarchical structures displaying both upward and downward causal influences" (Clegg, 2006, 167). The opposing theme in the literature is the European view which emphasizes "... how unorganized entities in a given system subjected to an externally imposed energy source seemingly organize themselves into structures that sustain or reproduce themselves for as long as the energy difference is maintained" (Clegg, 2006, 167).

The literature on complexity that refers to or focuses on engineering applications contains a relatively large quantity of work on the development of complexity models and analyses for specific applications or even distinct executions of an application. However, the work surrounding a more generic view of complexity in engineering systems is limited. Many works aimed at specific engineering applications refer to concepts such as static or dynamic complexity, yet the foundational literature on these concepts is not extensive. Two primary sources generically define concepts such as static and dynamic complexity. These sources are Wall (2009), who describes system complexity for chemical products, plants, and control systems, and Casti (1979, 97-125), who generically describe a basic approach on how to model various aspects of system complexity in large-scale systems.

There is a general consensus between Casti (1979) and Wall (2009) that complexity can be defined to first-order approximation as the combined contribution of the static complexity and dynamic complexity for a given system. Authors describe static complexity, or "structural complexity", as referred to by Wall (2009), as a measure of the "...structure of the systems communication channels and the interaction pattern of its component parts..." (Casti, 1979, 98). Static complexity measures the steady state topology of a system. Wall (2009) and Casti (1979, 98) both indicate that static complexity is influenced by the hierarchical structure, connectivity pattern, variety of behavior, and strength of interactions.[4] Wall (2009) and Casti (1979, 202) converge in their description of dynamic complexity as variations in a system's expected output occur over time. If the system's behavior or motion over time is in some way difficult to explain or predict, it is dynamically

[4] See sections III.3 and VI for a further discussion of these concepts.

complex. Wall (2009) indicates that dynamic complexity is the equivalent of the inverse of system robustness. System robustness is defined as "...the ability of a system to continue to operate correctly across a wide range of operational conditions, and to fail gracefully outside that range" (Gribble, 2001).

Static complexity and dynamic complexity are treated as the primary constituents of complexity; however, they are poorly connected. Authors make no attempt to more precisely define how each type of complexity mathematically combines to create the holistic complexity of a system. It is not transparent if they are additive, whether a more complex formula is needed, and if so, how situational the formulation needs to be. Also, it is not evident when static and dynamic complexity would be dependent or independent. Further, authors do not describe how to determine the relative importance of each type of complexity for a given system. For any given system, it is unlikely that each type of complexity contributes 50 percent to the total overall complexity. Each complexity uses significantly different metrics, and an approachable method of combining them would require that each type of complexity be on similar interval scales.

The literature reveals some additional forms of complexity that are not as consistently noted amongst authors. Of the selection, three forms of complexity are worthy of mention. Wall (2009) discusses another form of complexity referred to as operational complexity. Operational complexity is equivalent to structural complexity only that the focus is based on external elements to the system rather than internal elements. Operational complexity can be summed into the category of static complexity as long as its existence is acknowledged.[5]

Casti (1979, 105-106) discusses another important aspect of system complexity that is not necessary for first-order approximation of complexity, but is worth understanding. This second form of complexity is computational complexity, or the complexity associated with structure and size of

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[5] This is an assumption that will not be part of the analysis herein.

generating computable algorithms for a given system. Casti (1979, 120-122) has formulated several solutions for various types of system scenarios, but he notes that it is often that these derived computational methods cannot be applied because many systems do not exceed the limitations of the model.

Perrow (1999) is an extensive work investigating why certain systems experience unintended disasters. Perrow (1999, 78-86) advocates the consideration of another factor contributing to complexity that other authors do not address. Complexity can occur because of unintended and non-perceived interactions during implementation. This hidden complexity only becomes visible upon experience with the system. As problems arise, they must be dealt with and solved. As experience increases, the associated problems from unintended and non-perceived interactions diminish and the technological maturity of the process increases. The technological maturity of a given process or system plays a role in evaluating system complexity.[6]

III.2.2 Review of System Complexity and Lunar Oxygen Production

Existing literature on the production of oxygen on the Moon has not adequately considered any element of system complexity. The majority of available research on various specific processes suggests traits that can lead to system failure, reduced performance, and potentially higher overall complexity. As shall be further discussed in Sections VI.1, VI.2, and VI.3, this information can be particularly useful in understanding what factors negatively impact system performance in a wide variety of conditions, but it is not sufficient to support the full evaluation of system complexity.

Authors have drafted process diagrams for several processes which outline the overall topology of each process at varying levels of detail. Taylor and Carrier (1993) consolidate available knowledge for the known lunar oxygen extraction processes which includes information regarding potential risks and difficulties, as well as process diagrams for several of the processes. Taylor and

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6 This is an assumption that will not be part of the analysis herein.

Carrier (1993) is the closest work resembling a complexity analysis for lunar oxygen production, as the feasibility of each process is ranked based on a variety of factors, one of which is process conditions. There is not sufficient information in the existing literature to support a full system complexity analysis for any of the proposed lunar oxygen production processes. There is sufficient information, however, to begin making educated predictions about the future of system performance in the lunar environment and potentially problematic conditions. There is a wealth of literature on how system complexity can be measured. The previous ideas could be reshaped to create a foundational methodology for determining system complexity in lunar oxygen production systems.

III.3 Consensus on Static Complexity

This section further reviews the definition of static complexity as a measure of the structure and interaction of a system's communication channels, i.e., its steady state topology without considering any dynamic elements to the system. In Wall (2009) and Casti (1979, 98-102), there is a firm consensus that static complexity can be broken into four dimensions, as described below:

Hierarchical Structure: Measures the complexity associated with a given system's hierarchical organization. The complexity arises because of high rates of information processing and an increased requirement to assess the information with an increasingly complicated decision execution. The hierarchical structure is a huge overriding factor for static complexity, but it is not possible to measure when systems are only notional, as is the case with lunar oxygen production.

Interconnective Structure: Measures the complexity associated with the manner in which various components of a system are connected. It is a measure of the data paths in a system, how a particular data point interacts with another when isolated, and how information flows through the system. Note that a measure of the complexity of a system's interconnective structure does not measure the quantity of information that is running through a system, but rather the complexity in how the information is interconnected (Wall, 2009 and Casti, 1979, 99-100).[7]

Strength of Connections: The complexity associated with the relative strength of interactions between various components in a system. Smaller strength interactions, if small enough, may not add any "practical complexity" to the system. Likewise, it may be meaningful to isolate the components

[7] See section VI.1 for further discussion on this concept.

that are more problematic, based on a defined metric, and investigate the interaction pattern (Wall, 2009 and Casti, 1979, 101-102).[8]

Complexity in Variety: Measures the complexity associated with various manners a system can exhibit variety. Casti (1979, 100-101) notes a primary manner in which variety may translate into complexity in a industrial chemical system. Because a system's output can vary as a function of a system's input, variety in a system's input has the capacity to transform the variety in a systems output. Thus, a industrial chemical system can exhibit complexity through its variety in behavior (Wall, 2009 and Casti, 1979, 100-101).

Casti (1979, 102) comments that it becomes apparent that there are many dimensions in which a system can exhibit static complexity. A system may be complex in one dimension, but not complex in another, or it could be complex if used in a specified way. A view of static complexity from many dimensions results in greater transparency about the overall system complexity and what is specifically contributing to the static complexity.

The literature has dealt with each dimension of static complexity using numerous techniques. For measuring the static complexity associated with a system's interconnective structure, Casti (1979, 116-117) presents a baseline method using polyhedral Q-connectivity analysis. Q-connectivity analysis is an operational language of structure originally developed by Atkins (1974). Q-connectivity analysis is a means of interpreting the structural properties of relations between various sets. Gatrell and Beaumont (1982) comment that Q-connectivity analysis is not a technique or quantitative method, but rather it is an entire methodological perspective. The essence of structure is the interconnectivity between various elements of a given system. Thus, the basis of Q-connectivity analysis is being able to sufficiently describe the characteristic of interconnectivity. Individual interactions within the system are represented by various multidimensional figures (polyhedrals) (Gatrell and Beaumont, 1982).

A further investigation of the literature on q-connectivity analysis reveals that it is an application applied extensively to geographical applications, such as the distribution of pollution,

[8] See section VI.2 for further discussion on this concept.

social area analysis, road vehicle management, and man-environment relations (Beaumont & Gatrell, 1982). Casti (1979, 116-117) demonstrates the potential use of the method for more generic complex systems, but more detailed literature, Gatrell and Beaumont (1982), exists on how to apply q-connectivity analysis to various systems.

There is limited documentation supporting the determination of the strength of connections. Determining the strength of connections among interacting components appears to be a concept that is subjected to personal interpretation. This subjectivity occurs because strength of connections is dependent on which metrics are used to represent it. The direct literature surrounding strength of connections indicates many possible types of metrics can be used to determine the strength of connections, such as the proximity of components, which is used in the setting of system layout and design (Konz, 1990). Further investigation of the literature relating to industrial chemical systems reveals numerous other metrics that could be used to determine the strength of connections. One example is temperature variation across components. One concern with temperature is that it has the potential to affect the inter-phase concentration equilibria (Wall, 2009). However, no outstanding common metric for the purpose of determining connection strength has been identified relative to industrial chemical systems.

The literature surrounding the concept of complexity in variety is also limited, but there is a wealth of literature on process control for various engineering designs including industrial chemical systems. The proposed lunar oxygen production processes are not sufficiently developed to determine control system complexity, but there is an abundance of literature on process control and control structure for analogous industrial chemical processes. As examples, Sun et al. (1995) details the process control for the terrestrial hydrogen reduction of ilmenite for titanium. For processes analogous to carbothermal reduction, Prentice et al. (2012) details the process control for carbothermal production of magnesium. For molten silicate electrolysis, Lennin and Keppler (2002) outline the process control for a Zr/Hf magmatic process. For microwave extraction of polar permafrost, Haque (1998) blueprints the various process control mechanisms for microwave mineral treatment processes.

CHAPTER IV

SCOPE & ASSUMPTIONS

The overarching essential scope and assumptions implemented in this study are summarized below. Most of the summarized scope and assumptions are discussed in further detail throughout the text. Additionally, several smaller-scale assumptions are stated within the analysis.

- The context of this study is on the preliminary stages of lunar oxygen production where small oxygen production facilities are situated and solely used for the purpose of life support. This assumption is made because in the early stages of lunar oxygen production, only smaller scale lunar oxygen production facilities will likely be implemented.

- Four lunar oxygen production processes: hydrogen reduction of ilmenite, carbothermal reduction, molten silicate electrolysis, and microwave extraction of polar permafrost are chosen to demonstrate the application of the foundational methodology created in this study. [9]

- This thesis is not intended to evaluate which sources of oxygen and what lunar oxygen production process is ultimately superior for oxygen production on the Moon.

- The focus of this study on the element of static complexity, which is part of the greater concept of system complexity. This analysis does not ignore the importance of other essential considerations for system complexity e.g., dynamic complexity. [10] Nor does it ignore the importance of other essential considerations relevant to decision making. [11]

- Several general assumptions are made about complexity in this study. The general assumptions are:

    - It is assumed that the primary constituents of system complexity are static complexity and dynamic complexity. It is assumed to first order

[9] See section III.1.2
[10] See section I.3
[11] See section I.1

approximation that system complexity is the contribution of the static and dynamic complexity for a given system.[12]

- It is assumed that static complexity is defined by the combination of complexity associated with hierarchical structure, interconnective structure, complexity in variety, and strength of connections.[13]

[12] See section I.3.

[13] See section V.1.

CHAPTER V

METHODS

V.1 Investigating Three Dimensions of Static Complexity

To evaluate static complexity in lunar oxygen production, static complexity must be simplified and defined to make the analysis manageable. Because of the early stage of development in lunar oxygen production, it is not practical at this time to define every aspect of a lunar oxygen production system that contributes to static complexity, but the essential elements are captured in this analysis. As noted in the literature review, the definition of any type of complexity is highly subjective and can depend on the context of the study. For this study on lunar oxygen production, static complexity is defined according to the consensus of Wall (2009) and Casti (1979, 98-102). That is, static complexity is the combined contributions of complexity in interconnective structure, hierarchical structure, strength of connection, and variety in components. Thus, individual methods are chosen upon which to separately evaluate each dimension of static complexity and how to interpret the data. In this analysis, data from each dimension is held separate and not further combined.[14]

Hierarchical structure is difficult to evaluate in the current stage of lunar oxygen production development. To perform such an analysis, information about the hierarchical structure of the system and the overarching organizational body that is processing information and making decisions would need to be known. There is still much uncertainty about the variety and quantity of information, and the hierarchical structure that is necessary to accommodate the processing of that information and the

[14] Refer to the end of section VI.4.

execution of decisions. Thus, for this analysis emphasis is placed on developing methods to evaluate static complexity in only three of the components, i.e., interconnective structure, strength of connection, and variety in behavior, which are more tangible metrics to begin evaluating the current stage of research.

To evaluate static complexity associated with a system's interconnective structure, information contained in a system's process diagram[15] is converted into data matrices. Next, Q-connectivity analysis is applied to each of the data matrices to reveal its inherent interconnective structure and complexity. Casti (1979, 117) provides a formulation[16] that quantifies the overall complexity associated with a system's interconnective structure. If Q-connectivity analysis was to be applied to various lunar oxygen production systems, the generated complexity value could be compared for each system.

The analysis on interconnective structure also sets a framework for further analysis of strength of connections. A technique in Q-connectivity analysis, called a weighted relation, can be used to interpret the strength of connections between components. As part of applying the weighted relation, various metrics are discussed, such as change in temperature and distance between components that can be used to weight the relative strength of interactions in a system. Because of the limited information that is currently available for such an analysis, arbitrary values are chosen to demonstrate the application of a weighted relation. Following the weighted relation, a system's data matrix can be selectively filtered to reveal a new structure that may indicate something about the system's complexity that was not known by looking only at the system's original interconnective structure. The filtration is performed by using upper and lower bounded threshold values for the metric applied to remove interactions that do not fit within the boundary. Further, Q-analysis and

[15] See section V.2 for process diagrams.
[16] See section VI.1.

Casti's formulation can be applied to quantify the interconnective complexity of the resulting structure. The resulting interconnective complexity value can then be used as a measurement for the static complexity associated with strength of connections if caution is taken in carefully selecting filtration parameters that represent real properties of the system.[17]

To evaluate complexity of the variety in components, a simplistic method provided by Casti (1979, 101) is utilized. The method investigates the ratio in number of disturbances that can affect the equilibrium of a system compared to the number of control mechanisms capable of controlling the system's behavior in destabilizing circumstances. The greater the disturbance variety compared to the control variety, the more complex a system is with respect to variety in components. The potential disturbances and control mechanisms are pre-defined, which requires sufficient knowledge about the system and the environment with which the system interacts. In the current state of research, it is impossible to identify every potential disturbance and control mechanism that will exist in future lunar oxygen production processes. Thus, this analysis creates a preliminary framework to perform such an analysis when more information is present. Additionally, many of the known disturbances and process control mechanisms for the various lunar oxygen production processes provided in section III.1.2 are consolidated. Literature on lunar oxygen production and analogous terrestrial applications is reviewed to reveal information on disturbance and control variety.

This analysis on each dimension of static complexity provides three views into the system, each providing unique information about a system's static complexity. As discussed in the literature review, no author has attempted to aggregate these separate dimensions to create a holistic measurement of static complexity. Thus, a potential method to aggregate the results using the Single Multi-Attribute Ranking Technique (SMART) as part of Multi-Attribute Utility Theory is presented. Without such a technique, it is troublesome to place each dimension on comparable interval scales

[17] See section VI.2 for more explanation of this conclusion.

and to combine each dimension of complexity. However, it is worth noting that no technique can remove the element of subjectivity from this type of decision making method. With the SMART technique, a decision maker would be asked to identify his preferences for what attributes are seen to contribute more overall static complexity. Thus, caution must be exercised in capturing the subjective preferences of the decision maker.

V.2 Application of Notional Lunar Oxygen Production Systems for Methodology Demonstration

This section provides the starting process diagrams largely necessary for the interconnective structure and strength of connections pieces of the static complexity analysis. The process diagrams that are described below were created following a process diagram scheme similar to that of many of the diagrams in Taylor and Carrier (1993). Using a similar process diagram scheme focuses attention to the system's interconnective structure. The high-level process diagrams shown below demonstrate the interconnective structure and direction flow of the system. The various lunar oxygen production processes would need to be more deeply researched by later researches before more intricate detail of the components and interconnective mechanisms (piping, conveyors, etc.) can be diagrammed. However, these diagrams offer a basic starting template for static complexity analysis. Process diagrams for hydrogen reduction of ilmenite, carbothermal reduction, and molten silicate electrolysis, and microwave extraction of polar permafrost are utilized.

No process diagram has been identified in the literature for microwave extraction of polar permafrost. Thus, a process diagram is constructed using what knowledge is known about this process using professional consultation.

Figure 8 below is a legend for the process diagrams presented as Figures 9 through 12.

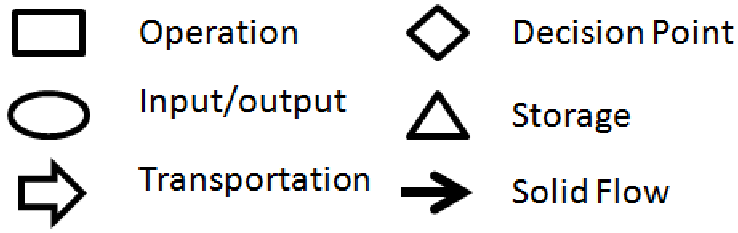

Figure 8: Process Diagram Legend

Figure 9 provides a process diagram for producing oxygen through hydrogen reduction of ilmenite. First, raw regolith is mined and beneficiated to produce sufficient quantities of ilmenite in a reactor feed hopper, and the tailings are sent to storage. In a reactor, the ilmenite is mixed with hydrogen gas under heat to yield steam (H_2O) and slag. The steam is electrolyzed to separate oxygen and hydrogen and the oxygen product is stored.

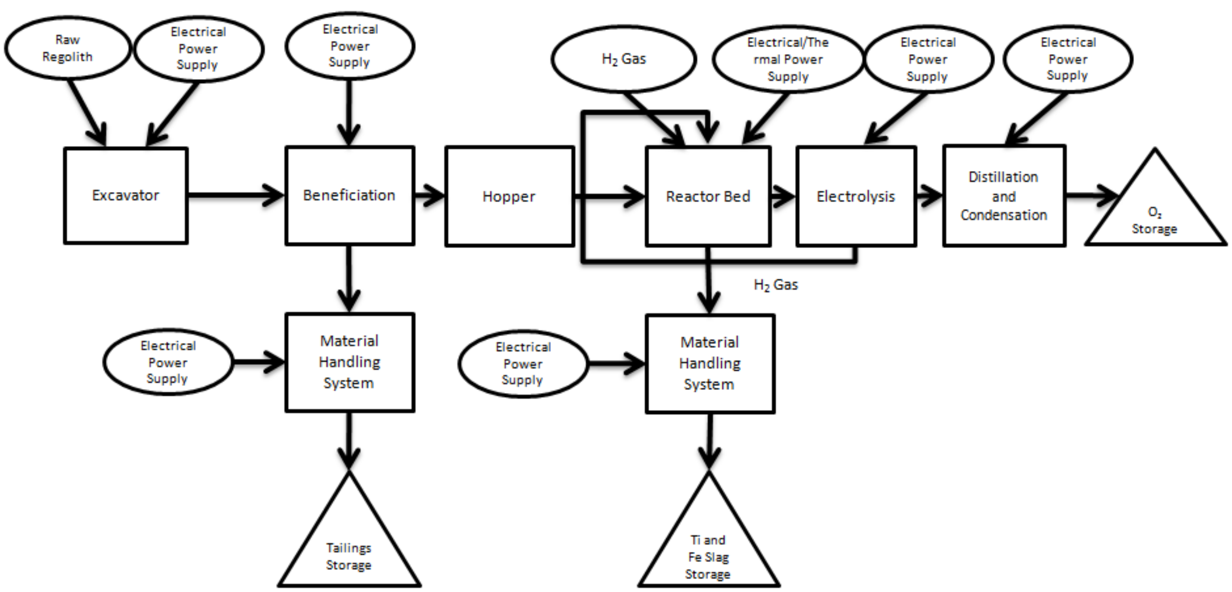

Figure 9. Hydrogen Reduction of Ilmenite (Modeled after Cutler & Krag 1985, Gibson & Knudson 1988, and Taylor & Carrier 1993).

Figure 10 provides a process diagram for producing oxygen through the carbothermal reduction of ilmenite. Similar to the hydrogen reduction of ilmenite process, raw regolith is mined and beneficiated to produce sufficient quantities of ilmenite in a reactor feed hopper, and the tailings are sent to storage. In a reactor bed or smelter, the ilmenite is mixed with organic refuge under heat. Iron decarburization and hydrocarbon reforming follow, yielding steam (H_2O) and iron. The water is then electrolyzed to yield oxygen and hydrogen for separate storage. The left over iron is forged into steel in the steel-making ladle so that the carbon reductant can be recovered. Steel and slag are byproducts of this process.

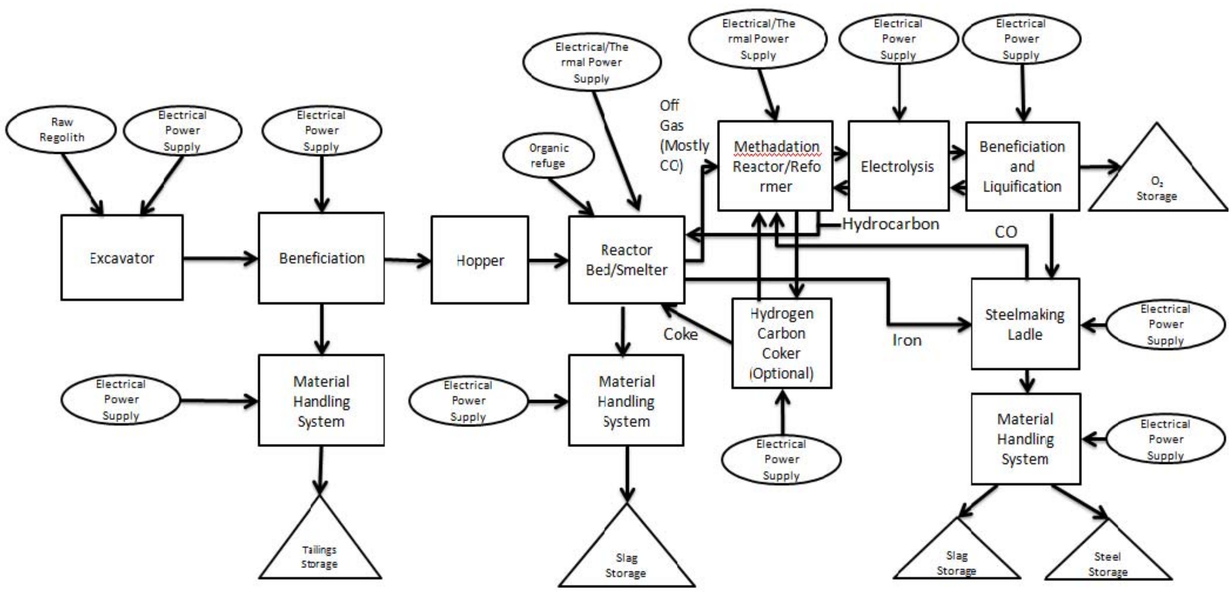

Figure 10. Carbothermal Reduction (Modeled after Cutler & Krag 1985, Gibson & Knudson 1988, and Taylor & Carrier 1993).

Figure 11 provides a process flow diagram for molten silicate electrolysis to produce oxygen. Again, raw regolith containing silicate minerals is mined and beneficiated to produce sufficient quantities of ilmenite in a reactor feed hopper, and the tailings are sent to storage. Under high heat, molten silicate feedstock is electrolyzed, yielding the oxygen product and slag in the form of iron.

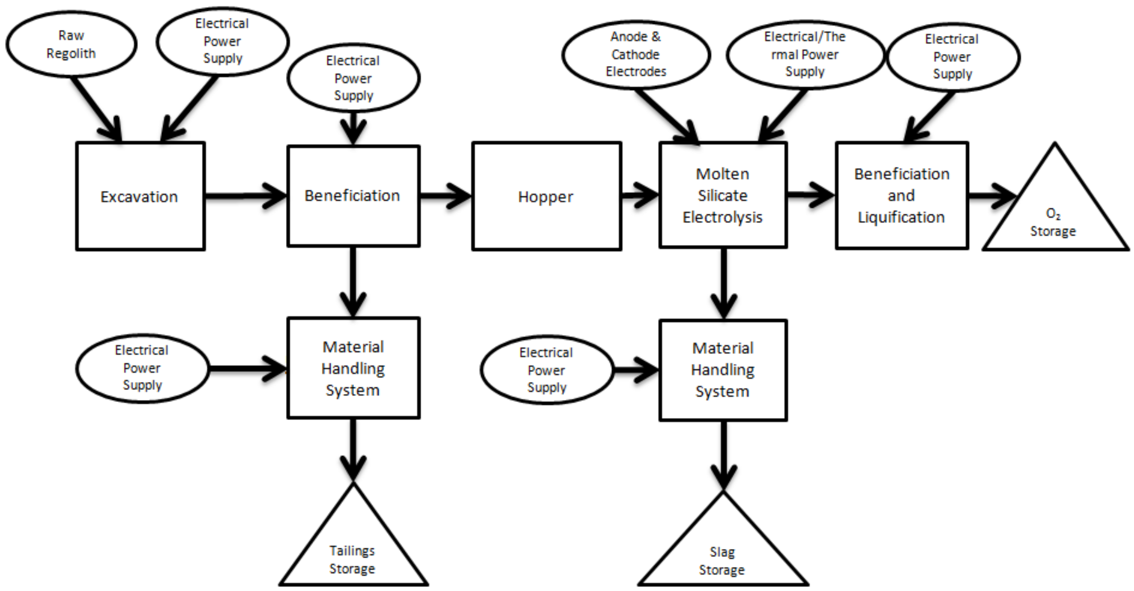

Figure 11. Molten Silicate Electrolysis (Modeled after Cutler & Krag 1985, Gibson & Knudson 1988, and Taylor & Carrier 1993).

Figure 12 provides a process flow diagram for microwave extraction of polar permafrost. Raw permafrost containing water is mined and the microwave processing is assumed to occur on the mining site. In a cold trap, the released water vapor and potential contaminates (composition uncertain) are captured and then electrolysis is performed to isolate the oxygen gas. The oxygen gas is then returned to the lunar base for further utilization.

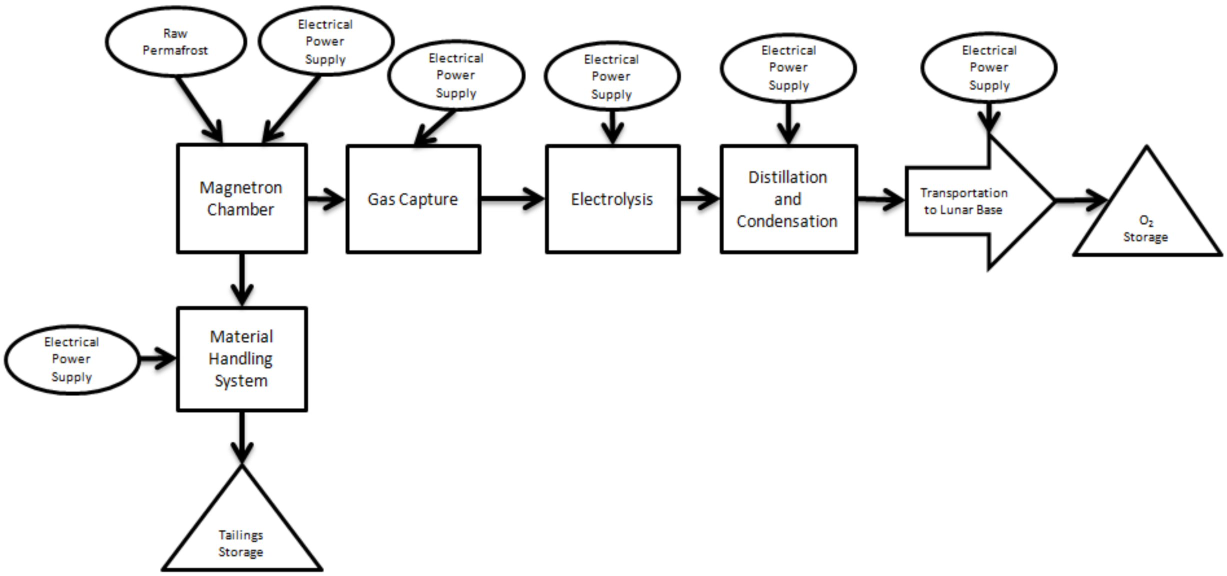

Figure 12. Microwave Extraction of Polar Permafrost (Dr. Mike Gaffey, personal communication, March 18, 2014, Modeled after Cutler & Krag 1985, Gibson & Knudson 1988, and Taylor & Carrier 1993).

CHAPTER VI

STATIC COMPLEXITY ANALYSIS

VI.1 Interconnective Complexity

VI.1.1 Understanding Interconnective Complexity through Q-Connectivity Analysis

Interconnective structure is one of the essential elements of static complexity. It defines the manner in which various components of a system are connected. Interconnective structure is a measure of the data paths in a system, how a particular data point interacts with another data point when isolated, and how information flows through the system. Measuring interconnective structure does not measure the quantity of information running through the system, but rather the complexity of the relationships among the components. Casti (1979, 117) proposes using Q-connectivity analysis as a means of measuring the interconnective structure of a system. This section demonstrates how Q-connectivity analysis can be used to interpret and quantify the interconnective structure of a lunar oxygen process.

In Q-connectivity analysis, describing interconnectivity is accomplished by translating system structure into a data matrix (an arbitrary data matrix is shown below in Figure 11. Further operations involve interpreting the data represented in the data matrix. The general steps in performing Q-connectivity analysis and further quantifying the complexity of the interconnective structure are summarized as follows:

- Establish the sets of data in which their interconnective structure are to be translated into a data matrix.
- Create a data matrix and set the rows and columns of the matrix so that the interconnectivities from the data set(s) are represented as intended.
- Translate the interconnectivities into the data matrix.

- Transform the data matrix into a shared-face matrix.
- Identify the q-connectivities at each dimensional level of the shared-face matrix and create a Q-vector describing the global structure of the q-connectivities.
- Apply Equation 8[18] to the Q-vector to quantify the complexity of the interconnectivities.

The steps are derived from Gartrell and Beaumont (1982) with the exception of the last point, which is derived from Casti (1979, 98-102). The following discussion demonstrates each of the above steps with a simplistic example. Then, as performed in section V1.1.2, the described process can be applied to quantify the interconnective complexity of lunar oxygen production processes.

Understanding Q-connectivity analysis begins with understanding how interconnectivity data can be translated into a data matrix. The below data matrix A (also notated λA) represents the interconnectivity between two sets of data X and Y. A set is a collection of elements and is notated by a capital letter (Gatrell & Beaumont, 1982). Elements from X are set as the rows of the data matrix and elements of Y are set as the columns of the data matrix. Data sets X and Y are defined below as:

$$X = \{X1, X2, X3, X4, X5, X6, X7\}$$
$$Y = \{Y1, Y2, Y3, Y4, Y5, Y6, Y7\}$$

In the data matrix, a "1" represents that there is an interconnection between an element of X and an element of Y. Conversely, a "0" indicates that there is no connection between an element of X and an element of Y. The values in the matrix were chosen to demonstrate the concept of interconnectivity, but do not represent an actual system. It is also acceptable to represent a single set of data on both axis of the data matrix. In that case, the data matrix would represent the interactions between individual elements of the single set. For example, if λA represented the interconnections between data set X and data set X only, then Figure 11 would feature Data Set X on both rows and columns. This scenario is the case for lunar oxygen production processes.

[18] Equation 8 is a formulation presented by Casti (1979) that can be used to quantify the connectivity of a given complex after a Q-vector has been constructed. Equation 8 is set forth later in this section.

λA	**Y1**	**Y2**	**Y3**	**Y4**	**Y5**	**Y6**	**Y7**
X1	0	1	0	0	0	0	0
X2	0	1	0	0	0	0	0
X3	1	1	0	0	0	0	0
X4	1	1	1	1	0	0	0
X5	0	0	1	1	1	0	0
X6	0	0	0	0	1	1	0
X7	0	0	0	0	1	0	0

Figure 13. Arbitrary Data Matrix A with Sets X and Y.

Several additional concepts must be defined and demonstrated. A ***simplex*** (plural is "simplices") is a collection of data set entries to which a designated data set entry in one set is related, including the designated data entry itself. A simplex is represented visually by a geometrical polyhedral (see Figure 14) and by a row in the data matrix. Figure 14 is a geometrical representation of the three-dimensional simplex on row four of Data Matrix A.

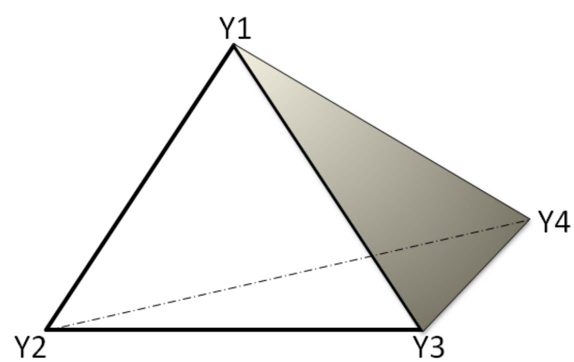

Figure 14. Three-Dimensional Simplex σ_3 (X4).

The purpose of representing interconnectivities with a polyhedral is purely for visual conceptualization. The ***dimensionality*** of a simplex is represented by the amount of vertices within the simplex. A ***vertex*** or vertices are the data set entries to which the designated data set entry is related. A vertex is represented by a column on the data matrix. A ***simplicial complex*** (or complex) is a set of simplices that are connected to the 0-level. A s***ystem*** is single complex or set of related complexes (Gatrell & Beaumont, 1982).

A simplex is notated in the following form as derived from Gatrell and Beaumont (1982):

$$\sigma_d(S) = \langle V1,V2,V3,...Vd \rangle$$

In the notation, σ denotes a simplex and the subscript d represents the dimensionality of the simplex. S represents the specified simplex in the data matrix. Figure 14 is a geometrical representation of the simplex σ3 (X4) of the data matrix presented in Figure 13. The data set entry X4 is connected to Y1, Y2, Y3, and Y4. The simplex is represented as row four on the data matrix and vertices are Y1, Y2, Y3, and Y4. A complex is notated in the following form (Gatrell and Beaumont, 1982):

$$KL_1\ (L_2;\lambda_A)$$

In the notation, K denotes the complex with simplices taken from L_1 = set X and vertices from L_2 = set Y, which are related via $\lambda_{A,}$ or data matrix A.

By investigating all simplices in Figure 13, it is apparent that they all share common vertices. For example, simplex σ_3 (X4) has common vertices Y3 and Y4 with σ_2 (X5). In this example, all simplices are connected to other simplices by at least a single shared vertex. Thus, all simplices can be joined to create a single complex. This conjoined complex is written as KX $(Y;\lambda_A)$. The geometrical representation of KX $(Y;\lambda_A)$ is shown below in Figure 15.

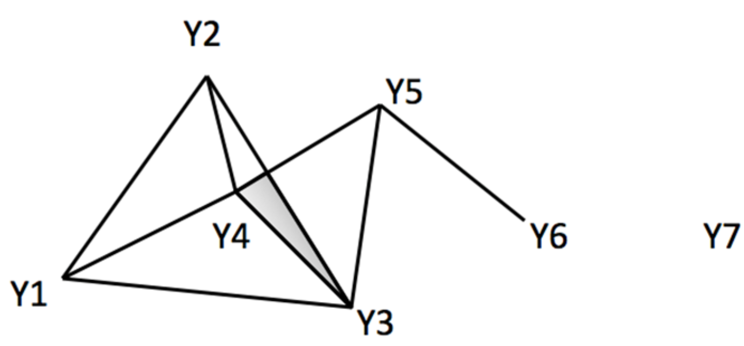

Figure 15. Geometrical Representation of Complex KX (Y;λA).

The matrix can also be adjusted to demonstrate the existence of multiple complexes within a system. To demonstrate, suppose that the matrix is cut by transforming all "1" values in σ_3 (X4) into "0" values (shown in Figure 14). The simplices in the data matrix form two complexes because all simplices are no longer connected by at least a single vertex. The new complexes are designated JX (Y;λ_B) consisting of simplices σ_0 (X1), σ_0 (X2), and σ_2 (X4), and HX (Y;λ_B) consisting of simplices σ_2 (X5), σ_0 (X6), and σ_0 (X7). The geometrical representations of JX (Y;λ_B) and HX (Y;λ_B) are shown below in Figure 17.

λB	**Y1**	**Y2**	**Y3**	**Y4**	**Y5**	**Y6**	**Y7**
X1	0	1	0	0	0	0	0
X2	0	1	0	0	0	0	0
X3	1	1	0	0	0	0	0
X4	0	0	0	0	0	0	0
X5	0	0	1	1	1	0	0
X6	0	0	0	0	1	1	0
X7	0	0	0	0	1	0	0

Figure 16. Arbitrary Data Matrix B to Demonstrate Two Disconnected Complexes.

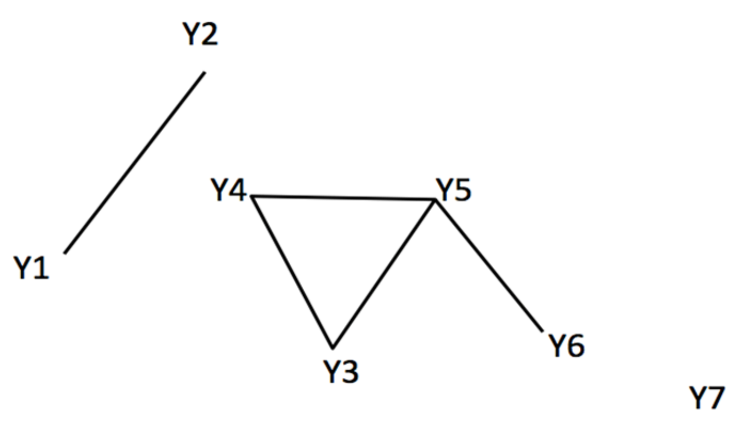

Figure 17. Geometrical Representation of Complexes JX (Y;λ_B) and HX (Y;λ_B).

Before investigating the Q-connectivities in Data Matrix A, the concepts of q-connectivity and q-face must be explored. As previously investigated, σ_3 (X4) of Figure 12 has two vertices in common with σ_2 (X5), which are Y3 and Y4 (a one-dimensional line). When two simplices share two vertices, they are a 1-face with each other. In Q-connectivity analysis, if two simplices share q+1 vertices (q = number of vertices), then they share a ***q-face***. The concept of a q-face is represented visually by a side of a geometrical figure, which makes intuitive sense. ***Q-connectivity*** means that two simplices are connected at a q-level, where q is defined by how many vertices they share (Gatrell & Beaumont, 1982).

The next step in Q-connectivity analysis is transforming the data matrix into a shared-face matrix and investigating the q-connectivities. A ***shared-face matrix*** is a symmetric matrix that represents all the direct q-connectivities between pairs of simplices in the original data matrix. Q-connectivity analysis can be performed without this matrix, but it is a tool that makes the q-connectivities more transparent and the analysis much easier to comprehend. Data Matrix A is transformed into a shared-face matrix shown below in Figure 18.

λ_A	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**
X1	0	0	0	0	-1	-1	-1
X2	0	0	0	0	-1	-1	-1
X3	0	0	1	1	-1	-1	-1
X4	0	0	1	3	1	-1	-1
X5	-1	-1	-1	1	2	0	0
X6	-1	-1	-1	-1	0	1	0
X7	-1	-1	-1	-1	0	0	0

Figure 18. Shared-Face Matrix for Data Matrix A.

Additionally, a shared-face matrix is constructed for Arbitrary Data Matrix B, which is shown in Figure 19 (Gatrell & Beaumont, 1982).

λ_A	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**
X1	0	0	0	-1	-1	-1	-1
X2	0	0	0	-1	-1	-1	-1
X3	0	0	1	-1	-1	-1	-1
X4	-1	-1	-1	0	-1	-1	-1
X5	-1	-1	-1	-1	2	0	0
X6	-1	-1	-1	-1	0	1	0
X7	-1	-1	-1	-1	0	0	0

Figure 19. Shared-Face Matrix for Data Matrix B.

In a shared-face matrix, a "-1" represents that there is no shared face between the simplices, a "0" indicates that a pair of simplices share a single vertex, a "1" indicates that a pair of simplices share two vertices, and so on. When creating a shared-face matrix, the data set entries representing the simplices from the original data matrix are projected on both axes. It is easiest to comprehend this matrix by starting at the diagonal and looking up and down the columns or left and right through the rows (Gatrell & Beaumont, 1982).

The primary interest lies in the structure of the entire complex, but first, the q-connectivities are revealed by performing Q-analysis on the complex. ***Q-analysis*** is performed by filtering the q-connectivities at each dimensional level beginning with the highest dimension and moving to a dimension of 0. At each dimensional level, the q-connectivities associated with that dimensional level and higher are identified (Casti, 1979, 71). Thus, for lower level q-connectivities, higher dimensional simplices are repeated because they have a dimensionality greater than or equivalent to the current q-level. The Q-analysis of λ_A is shown below using the q-connectivities identified in Figure 16. The results of the Q-analysis are discussed in the following discussion.

$$q = 3 : \{X4\}, \{X5\}$$
$$q = 2: \{X4\},\{X5\}$$
$$q = 1:\{X3,X4, X5\}, \{X6\}$$
$$q = 0: \{X1, X2, X3, X4, X5, X6, X7\} = \{all\}$$

At q=3, σ_3 (X4) and σ_3 (X5) are the only three-dimensional simplices, but neither is a 2-face with any other simplex. Or stated differently, there are no 3-connectivities between any of the simplices. Thus, σ_3 (X4) and σ_3 (X5) are disconnected at q=3. At q=2, σ_3 (X4) and σ_3 (X5) are the only simplices with a dimensionality of 2 or higher, but neither simplices is a 1-face (2-connected) or higher with any other simplex. At q=1, σ_1 (X3), σ_3 (X4), σ_3 (X5), and σ_3 (X6) are simplices with dimensionality 1 or higher. σ_1 (X3), σ_3 (X4), and σ_3 (X5) share a 0-face (1-connected) with one or more other simplices in the complex. Thus, σ_1 (X3), σ_3 (X4), and σ_3 (X5) are all connected at q=1. σ_3 (X6) has a dimensionality of 1, but is not 1-connected with any other simplex. Thus, it is disconnected from the other set. At q= 0, all simplices feature a dimensionality of 0 or higher and are all a -1-face (0-connected) with at least one or more other simplices. In this case, all simplices are connected at the 0-level.

Now that the q-connectivities have been identified at each dimensional level, a structure vector (referred to as a ***Q-vector***) can be created representing the global structure of the entire complex. To create a Q-vector, all disconnected sets of simplices are added at each dimensional level and the quantity at each dimensional level represents a value in the vector. The first value in the vector is the highest dimensional level and the last value is the dimension of zero. A Q-vector is constructed for $\boldsymbol{\lambda_A}$, which is shown below. The values above the vector designate the dimensional level of each entry of the vector (Casti, 1979, 117).

$$\begin{array}{c} \quad\;\; 3\ 2\ 1\ 0 \\ \mathbf{Q}\boldsymbol{\lambda_A} = \{2,2,2,1\} \end{array}$$

Casti (1979, 117) presents a formulation (shown below as Equation 8) that can be used to quantify the complexity of a given complex after a Q-vector has been constructed:

$$\psi(k) = {2\left[\sum_{i=0}^{N}(i+1)Qi\right]} \Big/ {(N+1)(N+2)} \tag{8}$$

N = dimension of the complex K (highest dimension in complex)
Q_i is the ith component of the q-analysis structure vector **Q**

Equation 8 holds true assuming the following axioms defined by Casti (1979, 117) are satisfied:

A. A system consisting of a single simplex has complexity 1.
B. A subsystem (subcomplex) has complexity no greater than that of the entire complex.
C. The combination of the complexes to form a new complex results in a level of complexity no greater than that of the sum of the complexities of the component complexes.

The above formulation calculates the complexity of a given complex based in reference to the most simplistic possible interaction, which is a single simplex. The 2/(N+1)(N+2) component of Equation 8 exists as a normalization factor satisfying axiom A. The generated value measures how many times more complex the measured complex is than a system consisting of a single simplex.

It is straightforward to calculate the complexity of the complex KX (Y;λ_A) as a value of 38/20 by applying Equation 8 to the structure vector $\mathbf{Q}\boldsymbol{\lambda_A}$. This type of calculation is provided below and will only be shown once for demonstration.

$$\psi(k) = (2)(1)(1) + (2)(2)(2) + (2)(3)(2) + 2(4)(2) \Big/ (3+1)(3+2)$$

$$\psi(k\mathrm{X}\ (\mathrm{Y};\lambda\mathrm{A})) = 2 + 8 + 12 + 16 \Big/ (4)(5)$$

$$\psi(k\mathrm{X}\ (\mathrm{Y};\lambda\mathrm{A})) = \mathbf{38/20}$$

Q-analysis can also be performed on the separate complexes in $\boldsymbol{\lambda_B}$, which are shown in Table 3. Casti (1979, 117) explains that with axioms A, B, and C present, Equation 8 can only be applied to a set of simplices that are connected at the 0-level (a complex). Thus, if the generated value in dimension 0 of the Q-vector is not 1, the equation cannot be applied. Instead, Equation 8 can be applied to each separate complex and the highest complexity value will represent the complexity for the system. The Q-analysis of λ_B is shown below using the q-connectivities identified in Shared-Face for Data Matrix B. The complexity for complex JX (Y;λ_B) is calculated to be 1 and the complexity for complex HX (Y;λ_B) is calculated to be 16/12, The complexity value 16/12 for λ_B is a lower value than the 38/20 value that is calculated for λ_A, which is intuitive as λ_A is a more deeply interconnected system.

Table 3. Sample Complexity Calculations.

Q-analysis of Complex JX (Y;λ_B)	Q-analysis of Complex HX (Y;λ_B)
q=1: {X3} q=0: {X1,X2,X3}	q=2: {X5} q=1: {X5}, {X6} q=0: {X5, X6, X7}
$\overset{\quad\quad 1\ 0}{\mathbf{Q}_{JX(Y;\lambda B)} = \{1,1\}}$	$\overset{\quad\quad 3\ 2\ 1}{\mathbf{Q}_{HX(Y;\lambda B)} = \{1,2,1\}}$
$\psi(JX(Y;\lambda B)) = 1$	$\psi(HX\,(Y;\lambda B)) = \mathbf{16/12}$

VI.1.2 Application of Q-Connectivity Analysis to Lunar Oxygen Production

Applying Q-connectivity analysis to lunar oxygen production involves the same procedure as outlined in section V1.1.1, but more explanation is provided to convert the interconnections in a lunar oxygen production process into a data matrix. In explaining how Q-connectivity analysis can be applied to complex systems, Casti (1979, 70-74) uses a simplistic analogy of animals in a predator-prey ecosystem. Understanding this analogy is helpful in understanding the application of Q-analysis to lunar oxygen production because a predator-prey ecosystem is inherently similar to a lunar oxygen production process.

A predator-prey ecosystem features a single defined set of species that experience predator-prey interactions. In the predator-prey ecosystem, there is one set of data containing all animals that exist within the ecosystem, and those animals exhibit interactions with each other rather than some other set of animals. A species can either eat another species, be eaten by a species, or both. Because one species will eat another species, there is a directional flow to the interconnections within the ecosystem. In representing predator-prey interaction in a data matrix, when one species eats another species, a "1" is placed in the corresponding position of the data matrix and a "0" is placed for no interaction.

This analogy is similar to a lunar oxygen process which contains interacting components that exhibit sending, receiving, or both sending and receiving actions. Further, because something is passed from one component to another, there is directional flow within the system. If a single set of data contains all components in a lunar oxygen production system, it follows that the interactions between those components could be represented in the same manner as predator-prey interactions. The manner in which Casti (1979, 70-73) applies Q-connectivity analysis to a predator-prey ecosystem is identical to the steps outlined in section V1.1.1, the only distinctions are that Casti uses two sets of data instead of one and Casti does not make use of the shared-face matrix. The use of shared-face matrix is derived from Gatrell and Beaumont (1982) to increase the transparency of the Q-connectivities, but was not presented as a tool in Casti (1979).

For this study, the interactions inherent in a lunar oxygen production process are represented by a single set of data because using a single set of data allows for the components to experience interconnective interactions with each other rather than with some other set of components. It is possible to imagine scenarios where there are multiple sets of interacting data, such as the interactions with a process controller and the components of a system. This analysis will focus on the high-level interconnectivity present in process diagrams for these notional processes. Based on the high-level interactions present in the process diagrams, splitting the various interacting components into multiple sets of data will not be necessary at that level of detail.

In the following sections, Q-connectivity analysis is applied to the high-level process diagrams originally presented in section V.2 for hydrogen reduction of ilmenite, carbothermal reduction, molten silicate electrolysis, and microwave extraction of polar permafrost. First, the process diagrams are modified to show how each component corresponds to an associated data set shown below each process diagram. Second, the interactions between components in the process diagram are translated into a data matrix using the corresponding data set entries. Next, each data matrix is transformed into a shared-face matrix based on the connectivity of the simplices in each original data matrix. Finally, Q-analysis is performed for each complex in each lunar oxygen production system (complexity calculations will not be shown, but are performed as outlined in section V1.1.1). The complex with the highest calculated complexity represents the interconnective complexity of the whole system. Further discussion is provided between each the figures and tables of the hydrogen reduction of ilmenite process for stepwise explanation. The same procedure is then performed on carbothermal reduction, molten silicate electrolysis, and microwave extraction of polar permafrost. A discussion summarizing each analysis follows each Q-analysis. Results are summarized in Table 8 and a concluding discussion is shown thereafter.

VI.1.2.1 Hydrogen reduction of ilmenite. Using the high-level process diagram for the hydrogen reduction of ilmenite, component numbers are added for each step in the process diagram as shown in Figure 18. Each of the components in Figure 20 corresponds to an entry in the data set $\mathbf{H}_{HRI}$ shown below the process diagram. Data set entry H1 corresponds to component 1 in Figure 18 and so on.

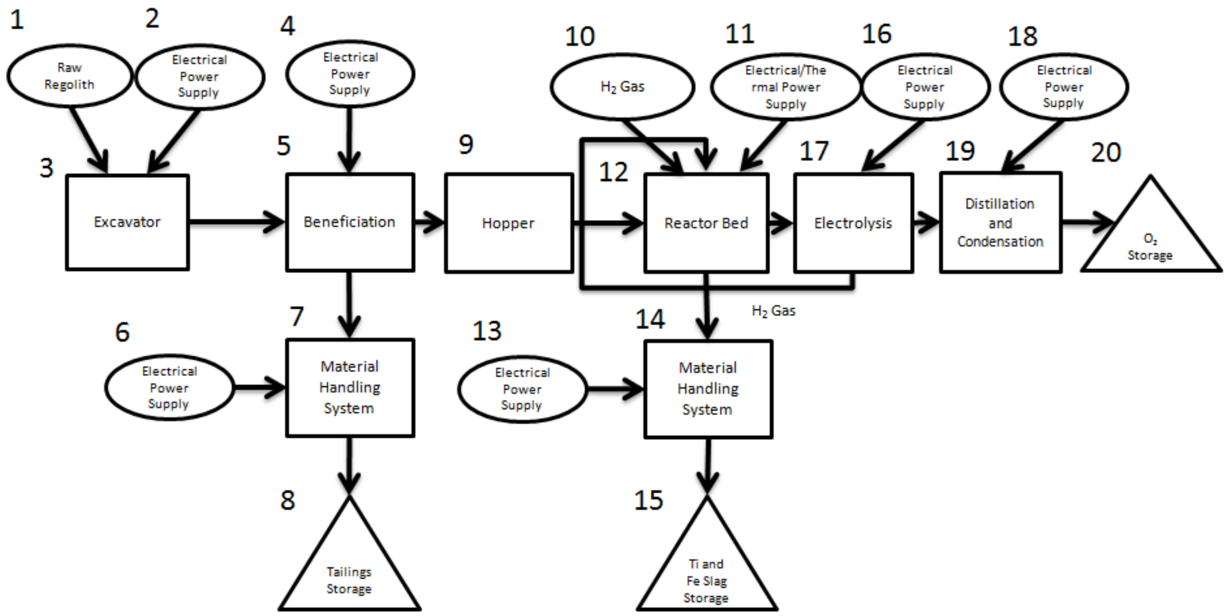

Figure 20. Hydrogen Reduction of Ilmenite with Component Numbers (Modeled after Cutler & Krag 1985, Gibson & Knudson 1988, and Taylor & Carrier 1993).

The data set for the hydrogen reduction of ilmenite is portrayed by the following formula:

$$\mathbf{H}_{\mathrm{HRI}} = \{H1, H2, H3, H4, H5, H6, H7, H8, H9, H10, H11, H12, H13, H14,H15,H16,H17,H18,H19, H20\}$$

A data matrix can be constructed to represent the interactions present in Figure 20 and is shown below as Figure 21. Additionally, a share-faced matrix can be constructed from Figure 21 and is shown as Figure 22. Discussion is provided thereafter explaining the creation of each matrix.

To explain the creation of Figure 21, some example interactions can be explored. Investigating the reactor bed (component 12) in Figure 20 shows that it is connected in the sending direction to components 14 and 17. Row H12 reveals that there is a “1” in the H14 and H17 entry representing the interactions. In addition, it is also transparent that numerous components are connected into H12. Or stated differently, H12 is connected in the receiving direction from numerous components. By investigating column H12, we can see that H9, H10, H11, H11, and H17 are connected to H12 as is the case in the original process diagram. Another connection to note is the backflow of hydrogen coming from component 17 (electrolysis) to component 12 (reactor bed). This connection can be represented in the data matrix by putting a "1" in the H12 position in row H17.

λHRI	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	H16	H17	H18	H19	H20
H1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H4	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H5	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
H6	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
H7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
H8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
H10	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
H11	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
H12	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0
H13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
H14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
H15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
H17	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0
H18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
H19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
H20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 21. Hydrogen Reduction of Ilmenite (HRI) Data Matrix

A shared-face matrix for hydrogen reduction of ilmenite is constructed as Figure 22 by investigating the Q-connectivities between each pair of simplices in Figure 21.

λHRI	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	H11	H12	H13	H14	H15	H16	H17	H18	H19	H20
H1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
X2	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
H3	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
H4	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
H5	-1	-1	-1	-1	1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
H6	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
H7	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
H8	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
H9	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1
H10	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1
H11	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1
H12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	0	-1	-1	0	-1	-1	-1	-1
H13	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1
H14	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1
H15	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
H16	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	0	-1	-1	-1	-1
H17	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1
H18	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1
H19	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1
H20	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

Figure 22. Hydrogen Reduction of Ilmenite (HRI) Shared-Face Matrix.

To restate, Q-connectivity represents the number of identical vertices shared between a pair of simplices. A simplex is a q-face of another simplex if they share q+1 vertices (where q is the number of vertices) with each other. In the shared-face matrix, a "-1" represents that there is no shared face between the simplices (-1-face), "0" indicates that a pair of simplices share a single vertex (0-face), a "1" indicates that a pair of simplices share two vertices (1-face), and so on. In Figure 21, the highest interactions between simplices form 0-faces with each other. Thus, the highest numbers in the shared-face matrix are 0's with the exception of a few "1" values on the diagonal indicating that a simplex is a 1-face with itself.

Q-analysis is applied to each complex in λHRI (Figure 19), as shown in Table 4. The complex with the highest complexity represents the complexity for the entire system. Discussion of the Q-analysis is provided below the Q-analysis.

Table 4. Q-analysis of Hydrogen Reduction of Ilmenite.

λHRI Complexes	λHRI Complexes
$H_{X1,x2}H(H;\lambda HRI)$ q=0 {H1,H2} Q={1} λ = 1	**$H_{H12,H13}H(H;\lambda HRI)$** q = 1 {H12} q = 0 {H12,H13} Q={1,1} λ = 1
$H_{H3,H4}X(H;\lambda HRI)$ q = 0 {H3,H4} Q={1} λ = 1	**$H_{H14}H(H;\lambda HRI)$** q = 0 {H14} Q={1} λ = 1
$H_{H5,H6}H(H;\lambda HRI)$ q = 1 {H5} q = 0 {H5,H6} Q={1,1} λ = 1	**$H_{H16}H(H;\lambda HRI)$** q = 0 {H16} Q={1} λ = 1
$H_{7H}(H;\lambda HRI)$ q = 0 {H7} Q={1} λ = 1	**$H_{H19}H(H;\lambda HRI)$** q = 0 {H19} Q={1} λ = 1
$H_{H9,H10,H11,H17,H18}H(H;\lambda HRI)$ q=1 {H17} q=0 {H9,H10,H11,H17,H18} Q= {1,1} λ = 1	

Investigating the connectivities for λ_{HRI} reveals that there are nine separate complexes identified for each system and no complex features a dimensionality higher than 1. Examining the simplices in hydrogen reduction of ilmenite reveals that there are only three simplices, σ_1(H5), σ_1(H12), and σ_1(H17), that feature dimensions higher than 0; all of which have a dimension of 1. As shown in the shared-face matrix for λ_{HRI} (Figure 20), none of these simplices is a 2-face (1-connected) with any other simplex in the data matrix. Additionally, neither of these one-dimensional simplices exists within the same complex. Because no more than one set of disconnected simplices exists at a dimensionality of 1, the complexity for each complex is 1. Stated differently, the resulting Q-vectors determined in the Q-analysis are in the form Q = {1,1,1...d), where d is the dimensionality of the complex. This form of a Q-vector will always result in a complexity of 1 when Equation 8 is applied. Because all complexes generate a complexity of 1, interconnective complexity for hydrogen reduction of ilmenite is 1.

VI.1.2.2 Carbothermal reduction. Using the high-level process diagram for carbothermal reduction, component numbers are added for each step in the process diagram as shown in Figure 23. Each of the components in Figure 23 corresponds to an entry in the data set $\mathbf{C}_{CR}$ shown below the process diagram.

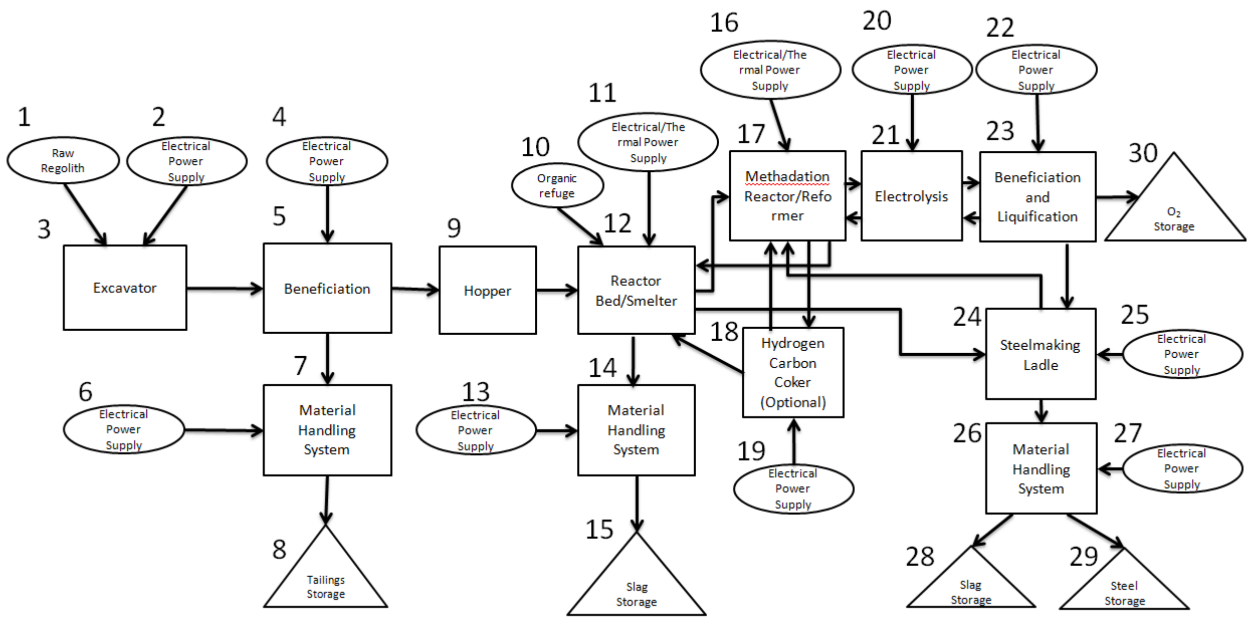

Figure 23. Carbothermal Reduction with Component Numbers.

A data matrix is constructed for carbothermal reduction and is shown in Figure 24.

λCR	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	X11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30
C1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C4	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C5	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C6	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C10	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C11	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C12	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
C13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
C17	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0
C18	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
C19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
C20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
C21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
C22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
C23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1
C24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0
C25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
C26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
C27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
C28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 24. Carbothermal Reduction (CR) Data Matrix.

The shared-face matrix for the carbothermal reduction is shown by Figure 25.

Λcr	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	X11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26	C27	C28	C29	C30
C1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C2	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C3	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C4	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C5	-1	-1	-1	-1	1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C6	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C7	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C8	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C9	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C10	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C11	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	2	0	-1	-1	0	-1	0	-1	-1	0	-1	0	-1	-1	-1	0	-1	-1	-1
C13	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C14	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C15	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C16	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	0	-1	0	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1
C17	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	2	0	0	0	-1	-1	0	-1	-1	-1	-1	-1	-1	-1
C18	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	0	-1	-1	-1	0	0	1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1
C19	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C20	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	0	-1	-1	0	-1	-1	-1	-1	-1	-1	-1
C21	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	0	-1	0	-1	-1	1	0	-1	-1	-1	-1	-1	-1	-1	-1
C22	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1
C23	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	0	-1	-1	0	-1	-1	2	-1	0	-1	-1	-1	-1	-1
C24	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	0	-1	-1	-1
C25	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	0	-1	-1	-1	-1	-1
C26	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	-1	-1	-1
C27	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	0	-1	-1	-1
C28	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
C29	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
X30	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

Figure 25. Carbothermal Reduction (CR) Shared-Face Matrix.

The data set for carbothermal reduction is portrayed by the following formula:

$$\mathbf{C}_{CR} =$$

$$\{C1,C2,C3,C4,C5,C6,C7,C8,C9,C10,C11,C12,C13,C14,C15,C16,C17,C18,C19,C20,C21,C22,C23,C24,C25,C26,C27,C28,C29,C30\}$$

Q-analysis is applied to each complex in λCR, as shown in Table 5. The complex with the highest complexity represents the complexity for the entire system. A discussion of the Q-analysis is provided below the Q-analysis.

Table 5. Q-analysis of Carbothermal Reduction.

λCR Complexes	λCR Complexes
$\mathbf{C}_{C1,C2}C(C;\lambda CCR)$ q=0 {C1,C2} Q={1} λ = 1	$\mathbf{C}_{C9,C10C11,C12,C13,C16,C17,C18,C19,C20,C21,C22,C23,C24,C25,C27}C(C;\lambda CCR)$ q = 2 {C17} q = 1 {C12}, {C17}, {C18},{C21},{C23}, {C24}, q = 0 {C9,C10,C11,C12,C13, C16,C17,C18,C19,C20,C21,C22,C23,C24,C25,C27} Q={1,6,1} λ = 2.7
$\mathbf{C_{C3,C4}C(C;\lambda CCR)}$ q = 0 {C3,C4} Q={1} λ = 1	$\mathbf{C_{C14}(C;\lambda CCR)}$ q = 0 {C14} Q={1} λ = 1
$\mathbf{C_{C5,C6}C(C;\lambda CCR)}$ q = 1 {H5} q = 0 {C5,C6} Q={1,1} λ = 1	$\mathbf{C_{C26}C(C;\lambda CCR)}$ q = 0 {C26} Q={1} λ = 1
$\mathbf{C_{C7}C(C;\lambda CCR)}$ q = 0 {H7} Q={1} λ = 1	$\mathbf{H_{H19}H(H;\lambda HRI)}$ q = 0 {H19} Q={1} λ = 1

Investigating carbothermal reduction reveals a more significant level of interconnectivity present within the interactions of its components in comparison to all other processes. In carbothermal reduction, the simplex with the highest dimensionality is $\sigma 3(C17)$, which has a dimensionality of 2. There are three 2-dimensional simplices, $\sigma 2(C9)$, $\sigma 2(C16)$, and $\sigma 2(C17)$, and four 1-dimensional simplices, $\sigma 1(C5)$, $\sigma 1(C21)$, $\sigma 1(C24)$, and $\sigma 1(C26)$. The 0-level connectivity reveals that the system is made up of four distinct complexes. Complex $C_{C9,C10C11,C12,C13,C16,C17,C18,C19,C20,C21,C22,C23,C24,C25,C27}C(C;\lambda CCR)$ is driving the higher complexity of carbothermal reduction.

Q-analysis of $C_{C9,C10C11,C12,C13,C16,C17,C18,C19,C20,C21,C22,C23,C24,C25,C27}C(C;\lambda CCR)$ calculates a complexity value of 2.7. This higher complexity value is derived primarily because the entire system features only sets of disconnected simplices at dimensions 1 and 2. These sets are disconnected because no simplex forms more than a 0-face with any other simplex. If several components were to form a 1-face, then some of the simplices would be connected at a dimension 1.

All simplices must be connected at the 0-level to form a complex, but the existence of more disconnected simplices at higher dimensions than 0 results in an increase in complexity. Effectively, when non 0-dimensional values of the generated structure vector Q are higher, the complexity of the represented complex is higher after application of Equation 8. This result demonstrates that having more interactions at higher interaction levels has the potential to increase complexity, but having increasingly more distinct sets of interactions and higher interactions levels is the primary driver for increasing the complexity. More directly, the highly connective nature of the reactor bed/smelter, the methadation reactor/reformer, and the steel making ladle, is driving the higher complexity. The highly connected interactions between these components allow for the higher dimensional interactions, and because those interactions are disconnected at higher dimensional levels, the overall complexity is much greater.

VI.1.2.3 Molten Silicate Electrolysis. Using the high-level process diagram for molten silicate electrolysis, component numbers are added for each step in the process diagram as shown in Figure 24. Each of the components in Figure 26 corresponds to an entry in the data set $\mathbf{M}_{mse}$ shown below the process diagram.

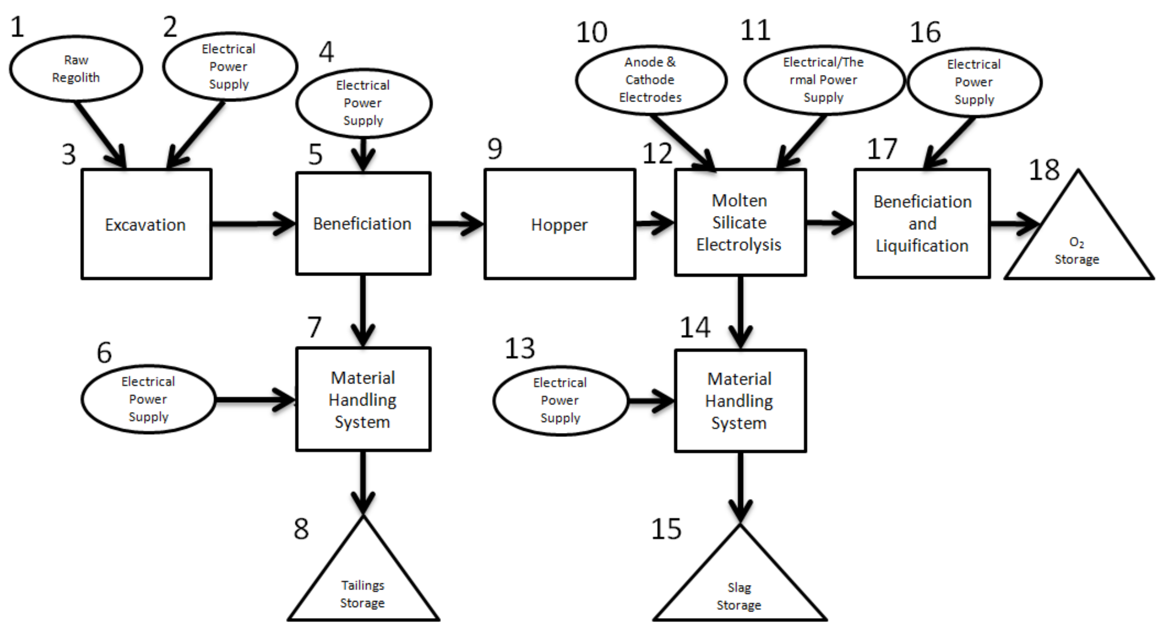

Figure 26. Molten Silicate Electrolysis with Component Numbers.

The data set for molten silicate electrolysis is portrayed by the following formula:

$$\mathbf{M}_{mse} = \{M1,M2,M3,M4,M5,M6,M7,M8,M9,M10,M11,M12,M13,M14,M15,M16,M17,M18\}$$

The data matrix for molten silicate electrolysis is shown in Figure 27.

λMSE	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18
M1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
M4	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
M10	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
M11	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
M12	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0
M13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
M14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
M15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
M18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 27. Molten Silicate Electrolysis (MSE) Data Matrix.

The shared-face matrix for molten silicate electrolysis is shown by Figure 28.

λMSE	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18
M1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M2	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M3	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M4	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M5	-1	-1	-1	-1	1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M6	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M7	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M8	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M9	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	-1	-1
M10	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	-1	-1
M11	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	-1	-1	-1	-1	-1	-1	-1
M12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	0	-1	-1	0	-1	-1
M13	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1
M14	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1
M15	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M16	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	0	-1	-1
M17	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1
M18	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

Figure 28. Molten Silicate Electrolysis (MSE) Shared-Face Matrix.

Q-analysis is applied to each complex in λMSE, as shown in Table 6. The complex with the highest complexity represents the complexity for the entire system. A discussion of the Q-analysis is provided below the Q-analysis.

Table 6. Q-analysis of Molten Silicate Electrolysis.

λMSE Complexes		λMSE Complexes	
$M_{M1,M2}M(M;\lambda MSE)$		**$M_{M9,M10,M11}M(M;\lambda MSE)$**	
q=0	{M1,M2}	q=0	{M9,M10,M11}
Q={1}		Q={1}	
λ = 1		λ = 1	
$M_{M3,M4}M(M;\lambda MSE)$		**$M_{M12,M13}M(M;\lambda MSE)$**	
q = 0	{M3,M4}	q = 1	{M12}
Q={1}		q = 0	{M12,M13}
λ = 1		Q={1,1}	
		λ = 1	
$M_{M5,M6}M(M;\lambda MSE)$		**$M_{M14}M(M;\lambda MSE)$**	
q = 1	{M5}	q = 0	{M14}
q = 0	{M5,M6}	Q={1}	
Q={1,1}		λ = 1	
λ = 1			
$M_{M7}M(M;\lambda MSE)$		**$M_{M16}M(M;\lambda MSE)$**	
q = 0	{M7}	q = 0	{M17}
Q={1}		Q={1}	
λ = 1		λ = 1	

The Q-analysis for molten silicate electrolysis reveals a similar story to hydrogen reduction of ilmenite. Two simplices, $\sigma_1(M4)$ and $\sigma_1(M9)$, have a dimension of 1, no simplex in λ_{MSE} features a dimensionality greater than 1, and neither is a 2-face (1-connected) with any other simplex (see Figure 27) or exists within the same complex. Investigating the interconnectivities for λ_{MSE} reveals that there are eight separate complexes identified for each system and no complex features a dimensionality higher than 1. Because no more than one set of disconnected simplices exists at a dimensionality of 1, the complexity for each complex is 1. The resulting Q-vectors determined in the Q-analysis are in the form Q = {1,1,1...d), where d is the dimensionality of the complex and this form of a Q-vector always results in a complexity of 1 when Equation 8 is applied.

VI.1.2.4 Microwave Extraction of Polar Permafrost. Using the high-level process diagram for microwave extraction of polar permafrost, component numbers are added for each step in the process diagram as shown in Figure 29. Each of the components in Figure 29 corresponds to an entry in the data set $\mathbf{M}_{MEPP}$ shown below the process diagram.

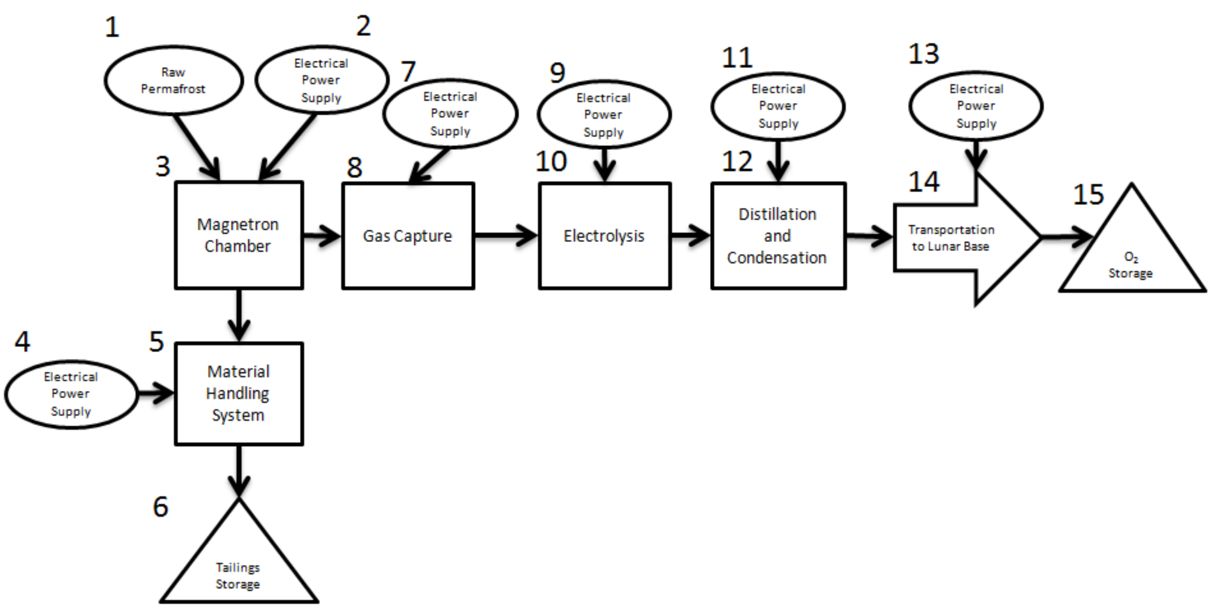

Figure 29. Microwave Extraction of Polar Permafrost with Component Numbers.

The data set for microwave extraction of polar permafrost is portrayed by the following formula:

$$\mathbf{M}_{MEPP} = \{M1,M2,M3,M4,M5,M6,M7,M8,M9,M10,M11,M12,M13,M14,M15\}$$

The data matrix for microwave extraction of polar permafrost is shown in Figure 30.

λMEPP	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15
M1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
M2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
M3	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0
M4	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
M5	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
M6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
M8	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
M9	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
M10	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
M11	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
M12	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
M14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
M15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 30. Microwave Extraction of Polar Permafrost (MEPP) Data Matrix.

The shared-face matrix for microwave extraction of polar permafrost is shown in Figure 31.

λMEPP	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15
M1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M2	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M3	-1	-1	1	0	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1
M4	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M5	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M6	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
M7	-1	-1	0	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	-1	-1
M8	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1
M9	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1
M10	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1
M11	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1	-1	-1
M12	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1
M13	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	-1	-1
M14	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1
M15	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

Figure 31. Microwave Extraction of Polar Permafrost (MEPP) Shared-Face Matrix.

The Q-analysis for microwave extraction of polar permafrost produces a similar result to hydrogen reduction of ilmenite and molten silicate electrolysis, as shown in Table 7.

Table 7. Q-analysis of Microwave Extraction of Polar Permafrost.

λMEPP Complexes	λMEPP Complexes
$M_{M1,M2}M(M;\lambda MEPP)$ q=0 {M1,M2} Q={1} λ = 1	**$M_{M10,M11}M(M;\lambda MEPP)$** q=0 {M10,M11)} Q={1} λ = 1
$M_{M3,M4,M7}M(M;\lambda MEPP)$ q = 0 {M3,M4,M7} Q={1} λ = 1	**$M_{M12,M13}M(M;\lambda MEPP)$** q = 0 {M12,M13} Q={1} λ = 1
$M_{M5}M(M;\lambda MSE)$ q = 0 {M5} Q={1} λ = 1	**$M_{M14}M(M;\lambda MEPP)$** q = 0 {M14} Q={1} λ = 1
$M_{M8,M9}M(M;\lambda MEPP)$ q = 0 {M8,M9} Q={1} λ = 1	

One simplex: $\sigma_1(M3)$ has a dimension of 1, no simplex in λ_{MEPP} features a dimensionality greater than 1, and neither is a 2-face (1-connected) with any other simplex (see Figure 31) or exists within the same complex. Investigating the connectivities for λ_{MEPP} reveals that there are seven separate complexes identified for each system and no complex features a dimensionality higher than 1. Because no more than one set of disconnected simplices exists at a dimensionality of 1, the complexity for each complex is 1. The resulting Q-vectors determined in the Q-analysis are in the form Q = {1,1,1...d), where d is the dimensionality of the complex and this form of a Q-vector always results in a complexity of 1 when Equation 8 is applied.

Performing Q-connectivity analysis and applying Equation 8 on the four notional processes, hydrogen reduction of ilmenite, carbothermal reduction, molten silicate electrolysis, and microwave extraction of polar permafrost is shown in Table 8.

Table 8. Summary of Q-Analysis Results.

Process	Q-Analysis of Interconnective Complexity
Hydrogen Reduction of Ilmenite	1
Carbothermal Reduction	2.7
Molten Silicate Electrolysis	1
Microwave Extraction of Polar Permafrost	1

The results reveal that carbothermal reduction is the only process to exhibit any significant interconnective complexity. Carbothermal reduction has a high interconnective complexity, not because it has more components, but because it has more disconnected sets of higher dimensional interactions. Hydrogen reduction of ilmenite, molten silicate electrolysis, and microwave extraction of polar permafrost feature the same interconnective complexity of 1, not because of a fault of Q-connectivity analysis, but because neither system has much interconnectivity at the level of scrutiny present in the high-level process diagrams.[19] Thus, the complexity is an artifact of the level of detail present in the process diagrams. If significant more detail was provided in the process diagrams, greater differences in complexity between hydrogen reduction of ilmenite, molten silicate electrolysis, and microwave extraction of polar permafrost would likely arise. Nonetheless, this demonstration provides a starting framework for the

[19] Further discussion is provided in the section VIII Recommendations on improving the transparency of complexity in the process diagrams for all the studied processes.

application of Q-connectivity analysis to determine the interconnective complexity of a lunar oxygen production process.

VI.2 Complexity with Strength of Connections

VI.2.1 Defining Strength of Connections

Section VI.1 detailed how Q-connectivity analysis and data matrices could be used to represent and quantify the interconnective complexity for lunar oxygen production systems. Complex systems contain numerous interacting components, but the relative strength of those interactions between those various components is also an important attribute. ***Strength of connections*** is defined as the relative strength of the interactions among various system components and hierarchical levels. Thus, some smaller interactions, although technically increasing a system's complexity by their existence, may actually contribute less complexity to the system. Strength of connections is measured based upon a dominating physical or measurable property between the interacting components and hierarchical levels (Casti, 1979, 101-102 and Wall, 2009). A system may feature no single ideal metric for measuring strength of connections, and there will likely be numerous potential candidates. As a result, determining strength of connections is subject to how the analyst wants to represent and interpret the system.

For the purpose of studying static complexity in lunar oxygen production systems, strength of connections is viewed through the perspective of complexity. Typically, complexity is viewed as an attribute that has negative consequences for the system. Wall (2009) indicates several possible outcomes that are associated with increased complexity in industrial chemical systems:

- Inability to deliver the desired quality (consistently)
- Failure to produce the desired production rate
- Failure to meet the desired safety
- Failure to meet the health requirements
- Substandard acute environmental performance
- Inability to meet the desired economic performance

Because the concept of complexity is the emphasis of this study and viewed as a negative attribute, the determination of strength of connections should be based upon the dominating physical and measurable properties between system components that potentially influence those possible outcomes.

Following the identification of metrics, Q-connectivity analysis provides a means to represent strength of connections for complex systems. Strength of connections can be represented by using what Gatrell and Beaumont (1982) define as a weighted relation**.** A ***weighted relation*** measures the relative strength between different relations on or between sets. The analysis presented in section V1.1 can be further expanded by applying weighted relations to notional examples of lunar oxygen production processes.

The weighted relationship itself may not be useful because the analysis does not indicate how the overall static complexity is being affected. The weighted relation only indicates which components have stronger interactions. The weighted relationship analysis has the potential to be more useful when a filtration technique is applied. By filtering the system's structure to isolate interactions, information may be revealed about a systems static complexity that was not previously transparent by just looking at the original interconnective structure. The filtration is performed by selecting limiting upper bounded or lower bounded threshold values for the metrics used to make the weighted relation and removing interactions that do not fit within the selected parameters. A new structure is then generated from the filtration. The resulting structure interconnectivity and the fragmentation (number of disconnected simplices at higher dimensional interactions) may indicate something new about the system's static complexity. Thus, Equation 8[20] may be used to quantify the complexity of the resulting structure.

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[20] See section VI.1.1.

Because there are numerous different metrics that can be selected, a large number of structures can be extracted from the system. The choice of the metrics and thresholds values allows the analyst to selectively isolate interactions and specific information in the system. Thus, metrics and threshold values should be chosen to yield information that is relevant to the possible negative outcomes of higher complexity as set forth above. A single number representing the complexity associated with strength of connections is desired. Therefore, it is assumed that if the decision maker can identify an optimal metric and set of thresholds, the resulting interconnective complexity of the filtered matrix will be used as a measurement for static complexity associated with strength of connections.

V1.2.2 Determining Strength of Connections

The ability to determine the strength of connections for the various lunar oxygen production processes under study is limited by the current immature state of development. There are numerous potential metrics available for measuring the strength of connections in lunar oxygen production systems. This section focuses on the application of weighted relations to lunar oxygen production. Additionally, several metrics are identified that could be used to determine strength of connections and guidance is provided for how those various metrics could inform a future analyst about various attributes of static complexity in lunar oxygen production systems. Further applications can be demonstrated when more information is known about these systems.

The general steps for applying a weighted relation and applying the filtration technique outlined by Gatrell and Beaumont (1982) are summarized as follows:

- Establish a single or set of data matrices upon which a weighted relation can be applied.
- Identify a single or set of metrics that is used to reduce the data matrices.
- Identify the threshold levels (slicing parameters) for each metric and determine whether the thresholds are upper or lower bounded.

- Adjust the data matrices to represent the measured data associated with each metric.
- For each metric, reduce the adjusted matrix to generate new structures.
- Investigate the interconnectivity of the generated structures to reveal information about the system. The slicing parameters can be adjusted to reveal new structures.
- Interpret the results.

Suppose that Data Matrix C shown in Figure 30 below represents the interconnectivity of a notional lunar oxygen production process. This notional example exhibits large temperature and pressure fluctuations between individual components because of the high temperatures of the reactors, the lower temperatures of cryogenic storage components, and the influence of the cold lunar environment. Temperature and pressure must be controlled precisely for optimal performance. Wall (2009) notes that temperature has the ability to affect the inter-phase concentration equilbria, but may affect the reaction rate and fluid dynamics differently. Additionally, large changes in pressure and temperature between components increase the difficulty to control the process and the probability of an equipment malfunction. Thus, increasingly larger variations in temperature across system components may increase the difficulty in controlling and maintaining system output. When the ability to control and maintain system output cannot be maintained, it could result in the inability to deliver the desired quality of oxygen, curtail the production rate of oxygen, fail to meet the desired economic performance, damage the metallurgical strength of the system components, and become a potential safety concern for astronauts. Therefore, inability to control and maintain a system's output has the potential to influence the occurrence of almost all negative outcomes of complexity noted in section V1.2.1. Since variations in temperature across components are a physical and measurable property that can influence the negative outcomes of complexity, it is one possible metric that can be used to evaluate the strength of connections between components in the notional example.

Assume that accurate data for change in temperature (ΔT) exist for each of the interactions within the notional system. Additionally, assume for each of the individual interactions that when a temperature variation surpasses a defined threshold value (separate values can be designated for each interaction), there is an increased potential for a failure. Set K represents the components of the process and the Q-analysis Data Matrix C and application of Equation 8 is shown in Figure 32 below.

λC	**K1**	**K2**	**K3**	**K4**	**K5**	**K6**	**K7**
K1	0	1	0	0	0	0	0
K2	0	1	0	0	0	0	0
K3	1	1	0	0	0	0	0
K4	1	1	1	1	0	0	0
K5	0	1	1	1	1	0	0
K6	0	0	0	1	1	1	0
K7	0	0	0	0	1	0	0

Figure 32. Arbitrary Data Matrix C with Set K.

K = {K1,K2,K3,K4,K5,K6,K7}

q = 3 : {K4}, {K5}
q = 2: {K4, K5}, {K6}
q = 1:{K3, K4, K5, K6}
q = 0: {K1, K2, K3, K4, K5, K6, K7} = {all}
3 2 1 0
Q = {2,2,1,1}
$\lambda = 1.7$

The first step in applying the weighted relation to this system is taking the notional ΔT data and transferring it to Data Matrix C. Transferring the temperature data is performed by taking the "1" values in the sample system, representing an interconnection, and replacing the "1" values with their associated notional ΔT data. Figure 33 shown below represents the adjusted Data Matrix C with notional temperature variations. For simplicity and because ΔT data does not currently exist for each of the lunar oxygen production systems, arbitrary values 1–5 represent ranges of temperature change

(ΔT). The values correspond to: 1 = Very Small ΔT, 2 = Small ΔT, 3 = Moderate ΔT, 4 = Large ΔT, 5 = Very Large ΔT.

λC	**K1**	**K2**	**K3**	**K4**	**K5**	**K6**	**K7**
K1	0	4	0	0	0	0	0
K2	0	5	0	0	0	0	0
K3	3	4	0	0	0	0	0
K4	2	4	3	1	0	0	0
K5	0	1	4	4	3	0	0
K6	0	0	0	1	4	4	0
K7	0	0	0	0	4	0	0

Figure 33. Arbitrary Data Matrix C with Notional ΔT Data.

The next step in applying the weighted relation is choosing a "slicing parameter", denoted by the symbol θ, which will "slice" Data Matrix C to reveal a new structure. A ***Slicing Parameter*** is a determined upper or lower tolerance for the applied metric that is used to remove or "slice" values from the matrix that do not fit above or below the boundary. The slice is performed because the resulting structure reveals the interconnectivities of the components which surpass that tolerance (Gatrell & Beaumont, 1982). The manner in which those resulting components are connected can provide information about how system attributes relate to complexity. To demonstrate: if the slicing parameter is chosen as $\theta = <3$, all values lower than 3 are removed from the matrix and replaced with "0"s. All remaining temperature values equal to or above 3 are then converted to "1" values. A new "sliced" structure is then generated. Different slicing parameters may be tested and the resulting generated structures will change depending on the selection of chosen slicing parameters.

The concept of applying a weighted relation and testing different slicing parameters is demonstrated below on the ΔT adjusted Data Matrix C using two different slicing parameters. For simplicity, the slicing parameters will represent the threshold for ΔT across the entire system.

However, ΔT thresholds could be set for each individual connection if so desired. First, the slicing parameter for the ΔT adjusted Data Matrix A is set to $\theta = >2$ as an upper boundary. Thus, all values of 2 and lower are converted to "0"s. When the system is sliced at $\theta = >2$, the following structure (Figure 34) is generated and its associated Q-analysis and application of Equation 8 is shown below the matrix.

λC	**K1**	**K2**	**K3**	**K4**	**K5**	**K6**	**K7**
K1	0	1	0	0	0	0	0
K2	0	1	0	0	0	0	0
K3	1	1	0	0	0	0	0
K4	1	1	1	0	0	0	0
K5	0	0	1	1	1	0	0
K6	0	0	0	0	1	1	0
K7	0	0	0	0	1	0	0

Figure 34. ΔT Adjusted Arbitrary Data Matrix C with slice at θ = >2.

<u>Q-analysis of Data Matrix C with θ = >2</u>

q= 3: {X5}

q = 2: {X4},{ X5}

q = 1:{X3, X4},{X5}, {X6}

q = 0: {X1, X2, X3, X4, X5, X6, X7} = {all}

$$\begin{array}{c} \quad 3\;2\;1\;0 \\ Q = (1,2,3,1) \\ \lambda = 1.7 \end{array}$$

If the slicing parameter is changed and set to $\theta = >1$ as an upper boundary, the structure shown by Figure 35 is generated and its associated Q-analysis and application of Equation 8 is shown.

λA	K1	K2	K3	K4	K5	K6	K7
K1	0	1	0	0	0	0	0
K2	0	1	0	0	0	0	0
K3	1	1	0	0	0	0	0
K4	1	1	1	1	0	0	0
K5	0	0	1	1	1	0	0
K6	0	0	0	0	1	1	0
K7	0	0	0	0	1	0	0

Figure 35. ΔT Adjusted Arbitrary Data Matrix C sliced at θ = >1.

<u>Q-analysis of Data Matrix C with θ = >1</u>

q=3: {X4}
q = 2: {X4},{ X5}
q = 1:{X3, X4, X5} , {X6}
q = 0: {X1, X2, X3, X4, X5, X6, X7} = {all}
3,2,1,0
Q = (1,2,2,1)
λ = 1.5

Investigating Figure 34 and Figure 35 with their associated Q-analyses, although immediately apparent, reveals that Figure 35 is less fragmented and more connected. This difference is the most apparent in the dimension 1 connectivities and by the generated λ values. In Figure 34, the simplices σ_3(K4), σ_2(K5), and σ_1(K6) are disconnected at q=1, because the simplices are not 2-connected (do not share a 1-face) with each other.[21] Stated more simply, the simplices do not share more than one common vertex. However, σ_3(X4) and σ_2(X5) are connected in Figure 35 because the simplices are 2-connected (share a 1-face) with each other. That is, the simplices share at least two common vertices. This difference in fragmentation is also apparent in the Q-vectors at the dimension 1 position. The Q-vector in to Figure 30 has a higher value of 3 compared to a value of 2 for Figure 33. Lastly, the resulting interconnective complexity for Figure 34 is higher than Figure 35. Thus,

[21] Refer to section V1.1.1 for more detailed discussions on q-connectivities and q-faces.

changing the slicing parameter produced different structures with varying levels of fragmentation and interconnective complexity. Also, both generated structures are different than the structure inherent in the original Data Matrix C.

All of the components of the notional lunar oxygen production process exist in such a space where they can be interconnected at different dimensional levels. Different types of relationships may exist between the components in this multidimensional space. There are relationships that occur at various different dimensional levels which are represented by the q-connectivities. There are also relationships that occur separately within an entire system because they are not connected by a common set of components. Such an example is the relationships between the reactor bed/smelter, methadation reactor/reformer, and steel making ladle in the carbothermal reduction process diagram, as shown in Figure 36.

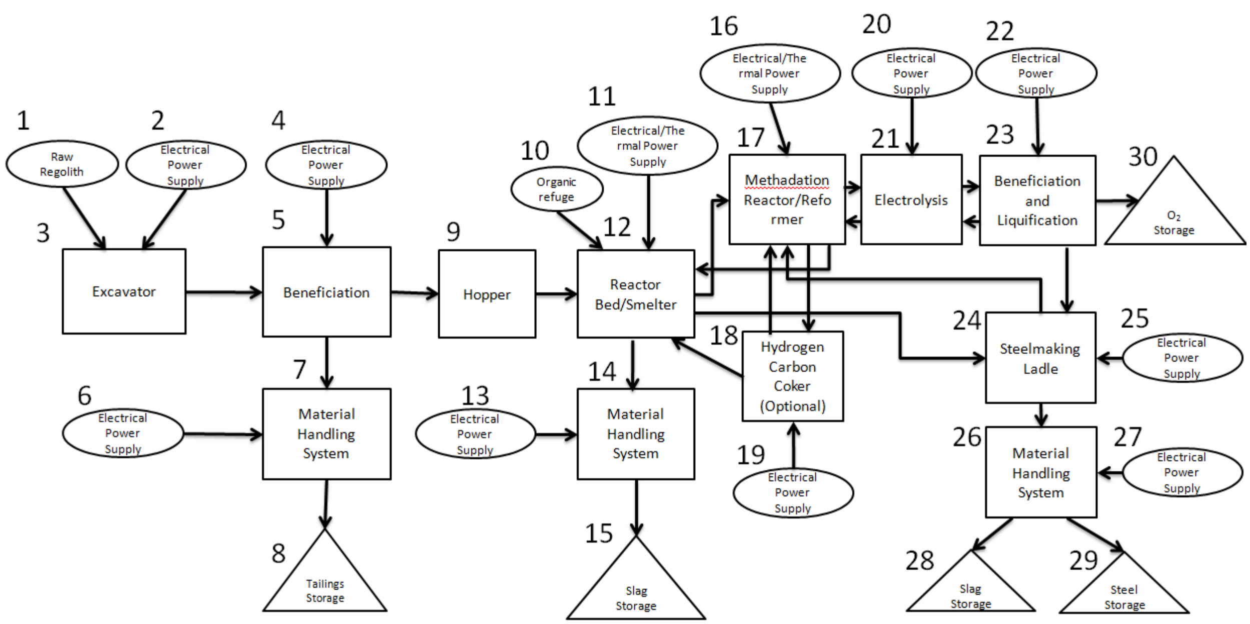

Figure 36. Carbothermal Reduction with Component Numbers

As an example, these subsystems are separate from interactions occurring with the beneficiation component. System behaviors, such as output control, may be related to such relationships between components. For this example, the response of the overall process control system is related to the number of interconnected components that exceed the defined threshold values for ΔT.

Industrial chemical systems, including the notional lunar oxygen production system used in this demonstration, exhibit an array of interacting components which are connected by numerous types of connection elements such as a piping, tubes, conveyors, or chutes. A temperature variation in one component, or connection, has the potential to influence many of the other components and connections within the system. As an example relevant to lunar oxygen production, consider a scenario where the quality of regolith being fed into the reactor was inconsistent. As a result of the inconsistency, the temperature inside the reactor may fluctuate significantly and the quality of the output products may also be inconsistent (Coughanowr & Koppel, 1965, 303-309). Thus, the temperature across the output connections could vary significantly in response to variations within the reactor. In general, wide temperature variations across the connections between components have the potential to cause the following problems within industrial chemical systems (Coughanowr & Koppel, 1965, 303-309):

- Temperature variations that surpass a defined limiting threshold may prevent the control and maintenance system from being able to compensate, resulting in a loss of performance or failure.
- Temperature variations that surpass a defined threshold across one connection have the potential to cause instabilities (including temperature variations) within other components and connections.
- Wide variations in temperature can change the metallurgical properties of the component's parts, causing wear and tear.

The threshold values for ΔT are determined by various considerations within the system and its environment. These considerations include (Richard J. Long, P.E., personal communication, March 18, 2014):

- The metallurgical properties of the connecting elements.
- Tolerance of the control system to various potential temperature variations that could occur within the system.

For the types of issues bulleted above, industrial chemical processes generally avoid close coupling between components and having little slack in variables. Buffers can be added to the system to reduce close coupling and input variability. However, the application of buffers has a limited capacity to counter the issues noted above (Perrow, 1999, 89-93).

The purpose of the slicing parameter as part of the weighted relation is to provide the flexibility to alternate between different scenarios when there is a change in sensitivity to variations in some parameter. The limited buffer capacity could reflect in the choice of a slicing parameter. For example, if several connecting elements with different tolerances to temperature variations were being considered, the corresponding ΔT thresholds of those connection elements could be tested on the system.

The application of a weighted relation in Q-analysis to this notional lunar oxygen production process provides the ability to say something useful about system control because it emphasizes the connectedness or fragmentation of the system. In the above demonstration, it is likely that the control system will run into further difficulty maintaining expected performance when highly connected interactions further exceed the limiting value for ΔT. Additionally, it is assumed that the control system has some inherent tolerance to variations in temperature. Thus, it is assumed that when the system interactions with respect to ΔT are 2-connected (a 1-face) or more, i.e., the simplices share at least two common vertices,[22] the system will exhibit greater control difficulties when the ΔT limits are exceeded.

In the above demonstration, changing the slicing parameter yielded two different structures with varying fragmentation at q=1 and resulting interconnective complexities. Lowering the slicing parameter yielded a system of less fragmentation. That is, there are more components that are a 2-

[22] Refer to section V1.1.1 for more detail and q-connections and q-faces.

connected (or a 1-face) with each other at q=1. The control system is assumed to run into further difficulty with increasing connectedness of interactions that exceed the limiting value for ΔT. Also, this temperature disturbance only occurs when the components in that relationship are 2-connected (a 1-face) or more. Therefore, it can be inferred that the control system will run into greater difficulty if the slicing parameter is lowered from θ = >2 to θ = >1. From an application standpoint, the slicing parameter could be changed because various connection elements with different metallurgical properties were being considered. The analysis would then suggest that the materials used to generate the slicing parameter of θ = >2 are preferable because the control system should be better able to maintain its expected performance. That is, multiples of the outlined methodology could be applied using several metrics instead of a single metric and the generated interconnective complexities could be averaged to create a holistic measurement for the complexity associated with strength of connections.

Ideally the decision maker can identify a single metric that best represents the strength of connections between components. When the weighted relation and filtration technique is applied using that metric, the resulting interconnectivity calculated using Equation 8 could be used as a metric for the complexity associated with strength of connections. The analysis is then dependent on what thresholds values are applied during the filtration. Thus, the decisions makers should identify thresholds that accurately represent the limitations of a system with respect to that metric. If a single metric cannot be identified, an average between multiple interconnective complexities could be used as a metric.

VI.2.3 Other Potential Metrics for Strength of Connections and Lunar Oxygen Production

The previous section demonstrated the application of a weighted relation a filtration technique for determining the complexity associated with the strength of connections between components in a lunar oxygen production system. The change in temperature (ΔT) across components was used in the demonstration, but there are numerous other metrics that can be used to determine other aspects of static complexity. A sample of alternate metrics includes, but is not limited to change in pressure, distance between components, the number of variables, mass requirements, and the flow rate between components. In the succeeding discussion, each metric is defined, the negative consequences associated with that metric are identified, and information is explained whether that metric was applied to lunar oxygen production system as part of a weighted relation analysis.

The ***change in pressure*** (ΔP) represents the degree to which pressure changes occur between components (Coughanowr & Koppel, 1965, 303-309). ΔP can be used as a metric for determining strength of connection for similar reasons as outlined in the ΔT discussion in section V1.2.1. Increasingly wider variations in pressure increase the stress on the materials composing the connecting elements and increases the difficulty of overall process control. Thus, applying a weighted relation and the filtration technique while using ΔP as a metric may provide further insight in how varying tolerances for pressure variations influence the static complexity of the system.

The ***distance*** between components represents the physical separation required between connected components (Konz, 1995, 64-65). It is possible that greater distances may increase the complexity of the system by requiring more materials and energy to move some substance or material between the interacting components. Additionally, the distance between components has the potential to influence the temperature, pressure, and state (gas, liquid, solid) of the material in the connecting element. Both scenarios would increase the complexity of process control. It is also possible that increased distances could act as a buffer which would reduce the complexity of process control. Further research into the process would need to be performed to identify which scenario is true. In the scenario where increased distances increases complexity, a weighted relation analysis would give insight into how varying tolerances for distances may affect the complexity. Having higher dimensional interactions between increasingly distant components would substantiate the need for more energy and materials and the complexity of process control.

The ***number of variables*** within a connection represents the number of elements that can be changed or controlled within that connection to ensure a successful product (Richard J. Long, P.E., personal communication, March 18, 2014). Increasing the number of variables within a connection increases the complexity of the overall process control by increasing the requirements for instrumentation and the number of parameters that need to be monitored. If a weighted relation and the filtration technique were applied to the system's interconnective structure, various tolerances for the number of variables that could be successfully controlled could be tested. The analysis would then indicate the impacts on the tolerances on the static complexity of the system.

The overall ***mass requirements*** represent the mass of all materials between the connected components (Richard J. Long, P.E., personnel communication, March 18, 2014). Higher mass requirements have a large impact on the overall complexity of the system because the increased mass of materials generally requires more machinery and more energy to operate. Thus, applying a weighted relation and the filtration technique would provide knowledge about how varying tolerances for more mass requirements may influence the presence of those negative consequences. It is likely that having higher-dimensional interactions between components that surpass the defined threshold for mass would substantiate the complexity of the system because the increased interconnectivity would result in needing more machinery and energy for successful operation.

The ***flow rate*** is the amount of a substance or material that can be passed from one component to another per unit of time (Coughanowr & Koppel, 1965, 303-309). It is possible that having a wide variety of flow rates would result in increased complexity in process control because of timing related issues. However, the flow rate may also act as a buffer and reduce the complexity. In the scenario that the process control complexity increases with higher variation in material flow rates, having higher dimensional interactions between components that surpass a defined threshold for flow rate would likely increase the complexity of process control and resource management. This increase in complexity occurs because visual observations of the connecting equipment over long distances may not be adequate. If a weighted relation and the filtration technique were applied, information could be gathered about how different tolerances for flow rates between various interactions would affect the overall static complexity of the system.

VI.3 Complexity in Variety

VI.3.1 Defining Complexity in Variety

The final dimension of static complexity is complexity associated with variety. Increased variety has potential to translate into increased complexity within a system. In a complex system, variety in its simplest form is the number of different types of components and connections (Wall, 2009). However, variety is a more expansive concept when it is considered in the light of an industrial chemical process because variety can manifest itself in numerous ways. Because the focus of this study is on static complexity, this section investigates how increased variety can translate into increased static complexity within a lunar oxygen production process.

The translation between increased variety and complexity is highly dependent upon the system and the setting in which the system operates because the way in which they interact can produce many different forms of variety. The important questions at hand are how can variety be translated into complexity in an industrial chemical process and what is the effect of the external lunar environment? The translation of variety into complexity with respect to lunar oxygen production can take many forms. In trying to capture every element of variety, the analysis may become too complex and one might lose focus of the essential elements that directly translate into complexity. Thus, it is logical to simplify the analysis to the essential manners in which variety can translate into complexity.

Returning to a statement by Casti (1979, 98), "...a system is complex if its components pieces (subsystems) are put together in an intricate and difficult-to-understand fashion." Casti (1979, 100-101) identifies a primary (not inclusive) manner by which variety can translate into increased complexity in a complex system. Variety can translate into complexity when the components and external environment interact in such a way that there is increased variety in behavior (Casti, 1979, 100-101). Variety in behavior arises from failure of a system to combat all potential perturbations. A system with low variety of behavior would not drift far from its expected or intended behavior. Whereas, if all perturbations could not be properly accommodated, then the system would experience a wider variety of potential behaviors. Casti's translation is intuitive because the focus is the actual behavior of the system.

Thus, for the purpose of the study, the analysis is simplified by investigating complexity associated with variety in behavior. ***Variety in behavior*** is defined as the ratio between the number of potential destabilizing disturbances to the number of stabilizing forces capable of restoring the system to optimal performance. A ***disturbance*** is any internal or external factor that can disrupt the system from optimal performance . A ***control force*** is any component or function in place to restore the system to optimal or suboptimal performance during a disturbance (Casti, 1979, 101). Determining variety in behavior for an industrial chemical process requires an adequate knowledge of the system's design, the external environment, and all known potential factors that are capable of destabilizing the system. Limited information exists about the variety of disturbances that the various lunar oxygen production systems may experience and the variety of control mechanisms in place to restore the system. Thus, the emphasis of this analysis is on demonstrating how variety in behavior can be determined for lunar oxygen production systems and identifying the disturbances and control forces that are currently known.

VI.3.2 Determining Variety in Behavior for Lunar Oxygen Production Systems

The general steps of determining variety in behavior for an industrial chemical process are stated below (Casti, 1979, 100-101):

- Identify all disturbances that could destabilize the system and the all components or control mechanisms capable of restoring stability to the system.
- Identify what modes of behavior (functions optimally, functions sub-optimally, and fails) the system exhibits when a control mechanism is applied during a given disturbance.
- Translate the identified behaviors, control mechanisms, and disturbances into variety in behavior matrix.
- Calculate the variety in behavior by Equation 9 (shown below).

To demonstrate this process, consider a simplistic sample lunar oxygen process represented by the symbol Σ. The controller for the system is defined as C_{Σ} and has three types of control inputs it can exhibit, which are defined arbitrarily as α, β, and γ. There are three types of potential disturbances that can impact the performance of the system, defined arbitrarily as 1, 2, and 3. When the control inputs are applied in response to a given disturbance, the system can exhibit three possible behaviors, defined as a, b, and c. The behaviors a, b, and c correspond to optimal performance, suboptimal performance, and system failure. These disturbances, control inputs, and behaviors can be translated to a matrix shown below as Figure 37 (Casti, 1979, 101). The Variety in Behavior Matrix C identifies which behavior modes a system exhibits when a particular control force is applied under a specified disturbance. It is assumed that there is always a desire for the system to exhibit an optimal performance mode of behavior when a disturbance is applied.

Control Type

Disturbance Type

C_Σ	**α**	**β**	**γ**
1	c	b	a
2	a	c	b
3	b	a	c

Figure 37: Variety in Behavior Matrix C

To calculate variety in behavior, an equation derived from Casti (1979, 101) can be applied. Casti (1979, 101) states that the only thing that can counteract increased variety in behavior is increased variety in controlling actions. The below formulation shown as Equation 9 is referred to as the law of requisite variety and is derived from cybernetic theory (theory of systems and their structures) (Casti, 1979, 101).

$$Variety\ in\ Behavior \geq \frac{Disturbance\ Variety}{Control\ Variety} \tag{9}$$

Thus, increased variety in behavior in a system is generated when there are more disturbances than can be accounted for by the control inputs. The application of this procedure can be applied to lunar oxygen production processes when sufficient information is available about the potential disturbances that can influence the stability of the system and when all controlling actions capable of restoring the system are known. A selection of known potential disturbances and controlling actions for the lunar oxygen processes are presented in the next section.

VI.3.3 Identifying Known Disturbances and Control Variables for Lunar Oxygen Production Systems

Tables 9 through 12 presented below list numerous possible disturbances and control variables with their associated sources for the hydrogen reduction of ilmenite process, carbothermal reduction, molten silicate electrolysis, and microwave extraction of polar permafrost, respectively.

These disturbances and control variables are derived from analogous terrestrial applications of similar processes and from consolidated research about lunar oxygen production, such as Taylor and Carrier (1993). These disturbances and control variables can be expanded as research evolves.

Kang, et al. (1995) present information discussing the hydrogen reduction of natural ilmenite (terrestrial ilmenite) in a fluidized reactor bed to extract titanium and titanium compounds. Terrestrial ilmenite extraction for titanium and titanium compounds is highly analogous to extracting oxygen on the lunar surface, and many of the disturbances and control variables are identical. Prentice et al. (2012) presents information regarding the carbothermal production of magnesium using CSIRO's (Commonwealth Scientific Industrial Research Organization) Magsonic process which involves the supersonic quenching of magnesium vapor. Though no direct literature has supported the use of supersonic quenching in lunar carbothermal production, many of the same process disturbances and control variables should be identical in lunar carbothermal reduction. Linnen and Keppler (2002) outlines the melt composition control in Zr/ Hf magmatic processes. Though Zr/Hf magmatic processes are not identical to the silicate oxides used in lunar molten silicate electrolysis, there are still many similar process control variables and disturbances that can be extrapolated by looking at the terrestrial counterpart. Haque (1999) extensively details microwave energy for mineral treatment processes which includes information about potential disturbances and control variables. Microwave treatment for mineral process shares similarities to that of lunar microwave extraction of polar permafrost.

Kang, et al. (1995) note a set of common disturbances associated with any fluidized bed reactor. Variations in particle size, ore quality, and composition can disturb the temperature, pressure, and reaction rate. In a fluidized bed reactor, gas is passed through the reactants at high velocities which results in a pressure differential within the reactor. The pressure differential can vary in response to changes in temperature, the reaction rate, and variations in ore composition and size. Another disturbance associated with fluidized bed reactors is retardation in the early stages of the reduction due to mixing of gas, particles, and foreign elements (Kang et al. 1995). Works more specific to lunar oxygen production note problematic contaminates (Trolite (FeS), MgO, and Cr) that can disturb the reaction and cause damage to the reactor lining. Taylor and Carrier (1993) note that a potential problem exists with the retention of hot hydrogen within the system. Even small leaks on the Moon could result in a loss of large quantities of hydrogen gas. Potential disturbances relative to the electrolysis cell are undesirable impurities that are not successfully distilled. These impurities would be volatiles trapped in the soil, but they exist in trace quantities on the moon and will not likely be a major concern (Dr. Mike Gaffey, personal communication, March 25, 2014).

For a fluidized bed process, the primary control variables that influence temperature, pressure, and the reaction rate are the H_2 gas velocity, the internal reactor temperature, and the output through the gas flow control valve. There is a strong relationship between the H_2 gas velocity, the reaction rate of ilmenite reduction, and the internal pressure differential. A higher velocity of H_2 gas decreases the reaction rate of the ilmenite, and increases the pressure differential within the reactor. Increasing the reactor temperature increases the average pressure within the reactor and increases the reaction rate of ilmenite reduction. Adjusting the output gas flow control valve to let more or less gas out per unit of time decreases the average internal reactor pressure, decreases the reactor temperature, and will result in slowing the rate of reaction of the reduction of ilmenite (Prentice et al., 1995). The only identified control variable for electrolysis control is the amount of electrical current used to electrolyze the extracted water. With regard to ilmenite beneficiation and water purification and liquefaction, limiting the presence of reactor contaminates and impurities is best prevented with successful beneficiation with a crusher and electrolysis purification (Christiansen et al., 1988).

Table 9. Consolidated List of Disturbances and Control Variables for Hydrogen Reduction of Ilmenite.

Disturbances	Control Variables
• Variations in reaction rate (Kang et al., 1995) • Variations in temperature (Kang et al., 1995) • Variations in pressure (Kang et al., 1995) • Variation in particle size distribution (Kang et al., 1995) • Variation in ore quality (% ilmenite) (Kang et al., 1995) • Retardation of the reductant in early stages (Kang et al., 1995) • Pressure differential across reactor bed (Kang et al., 1995) • Presence of contaminates (Trolite (FeS), MgO, and Cr) (Taylor & Carrier, 1993, 81-84) • H_2 gas leaks (Taylor & Carrier, 1993, 81-84) • Impurities in electrolysis cell (Taylor & Carrier, 1993, 81-84)	• Gas velocity of H_2 gas (Kang et al., 1995) • Reactor temperature (Kang et al., 1995) • Reactor pressure (Kang et al., 1995) • Quantity of feedstock (Kang et al., 1995) • Electric current (electrolysis cell) (Taylor & Carrier, 1993, 81-84)

One of the primary disturbances noted by Prentice, et al. (2012) for the general carbothermal process is the potential for the reaction to reverse. Although not spontaneous, the reaction can be disturbed and reverse its direction. Another problematic issue with the carbothermal process noted by Prentice et al. (2012) is the potential for gas exit nozzle blockage. Magnesium and other impurity metals found in lunar regolith may have the same potential for gas exit nozzle blockage. Magnesium and other impurity metals condense on the surface and turn into oxides at high melting points, but this is only a problem when the temperature is high enough for condensation. Other potential problems include variations in reaction rate, temperature, and pressure across the numerous reactors in the carbothermal process.

The chemistry for magnesium production is shown below:

$$MgO + C \leftrightarrow Mg + CO \tag{10}$$

Magnesium is also present in Mg_2SiO_4 and MgO. The chemistry for lunar carbothermal reduction of Mg_2SiO_4 is shown by the following reactions:

$$(Mg, Fe)_2SiO_4 + 2CH_4 \leftrightarrow 2(MgO,FeO) + Si + 4H_2 + 2CO \tag{11}$$
$$CO + 3H_2 \leftrightarrow CH_4 + H_2O \tag{12}$$
$$H_2O \leftrightarrow H_2 + 1/2O_2 \tag{13}$$

A potential control variable that can be used to counter the possibility of reversion in carbothermal reduction is the rapid cooling of the gaseous products. Potential variables for cooling are heat transfer with surfaces or by shock-chilling by dilution using such diluents as natural gas or nitrogen. Pressure in the reactor (smelter) is predominantly maintained by the control valve on the gas flow through the gas exit nozzle. Reactor (smelter, reformer, and coker) temperatures are maintained through applied electrical power to an induction furnace. The reaction rate (smelter) can be controlled by adjusting the size of the reactor bed and to a lesser extent by the inert gas flow rate. With the water electrolysis phase, the only identified control variable is adjusting the electrical current (Taylor and Carrier, 1993).

Table 10. Consolidated list of Disturbances and Control Variables for Carbothermal Reduction (Prentice et al., 2012).

Disturbances	Control Variables
• Reactor goes into reversion (reverse direction) • Variations in reaction rate • Gas nozel blockage (particularly with magnesium • Variations in Pressure (smelter, reformer, and coker) • Variations in temperature(smelter, reformer, and coker)	• Minimized cooling of gaseous reaction products (Heat transfer, shock-chilling) • Inert gas flow rate • Gas exit nozzle flow rate • Reactor bed size • Heat of induction furnace (smelter, reformer, and coker) • Electric current (electrolysis) Taylor & Carrier, 1993, 88-90)

Linnen and Keppler (2002) identify several disturbances associated with magmatic processes. With silicate melt processes, the melt solubility, diffusivity, and conductivity are highly dependent upon the composition of the feedstock and to varying degrees with temperature. In a magmatic process, a lower solubility results in decreased melt activity and increased time for silicate diffusivity. Melts with higher heat capacity require less energy to heat the material to the desired temperature. Conductivities in tested laboratory melts for lunar molten silicate electrolysis suggest that conductivity can vary over a range of two orders of magnitude. Other variations noted within magmatic processes are variations in reactor temperatures and pressure largely due to variations in melt composition and melt granule size (Linnen & Keppler, 2002).

The primary control variable for molten silicate electrolysis is the electric current between the two electrodes. Increasing the current increases the temperature within the electrolysis cell and increases the rate of silicate diffusion and thus the release of water (Haque, 1999). In general, increasing concentrations of SiO_2, Al2O3, and FeO in the melt requires more energy to heat to the desired temperature (Taylor & Carrier, 1993, 88-90). The other identified control variable is the selective beneficiation of the regolith composition to yield a more desirable and consistent melt composition. Lastly, the controlled use of a flux agent such as cryolite can be used to dissolve the silicate feedstock which decreases the required operating temperatures, increases the conductivity of the melt, and alleviates some of the difficulties with high temperature corrosion (Taylor & Carrier, 1993, 88-90 and Dr. Mike Gaffey, personal communication, April 26).

Table 11. Consolidated List of Disturbances and Control Variables for Molten Silicate Electrolysis (Linnen & Keppler, 2002).

Disturbances	Control Variables
• Variations in temperature • Variations in Pressure • Variations in melt solubility • Variations in diffusivity of silicates • Variations in melt conductivity (Taylor & Carreir, 1993) • Variations in melt granule size	• Current between electrodes • Adjusting melt Compositions • Controlling temperature with fluoride flux (Taylor & Carrier, 1993)

Variations in heating rate could potentially occur within the microwave chamber. Heating rate is largely a function of composition of the materials exposed to the microwave radiation. Haque (1999) notes that silicates, carbonates, sulphates, and some oxides do not easily generate heat, but most sulfides, sulfosalts, and arsenides tend to generate heat quite well. The presence of varying compounds in addition to polar water ice will likely affect the heating rate. Variations in particle size have the potential to influence the heating rate of a material, but it is not a consistent factor. Some material compositions may heat faster with coarser material, and some may heat faster when the material is finer (Haque, 1999). Another potential problem is the evaporation of contaminates in the electrolysis of water. The potential evaporation contaminates largely depend upon the composition of the lunar polar ice. The LCROSS mission discovered varying concentrations of ammonia, methane, and hydrocarbons, which have the potential to contaminate the electrolysis evaporates (Colaprete et al., 2010 and Dr. Mike Gaffey, personal communication, March 25, 2014). An additional disturbance is the potential for a thermal runaway within the microwave chamber. A thermal runaway occurs when non-homogenous materials (in terms of dielectric property) heat at different rates within the microwave chamber. Lastly, there is the potential for variations in temperature and pressure (assuming the microwave chamber is pressurized) within the microwave chamber (Haque, 1999).

Haque (1999) identifies several control variables capable of balancing the potential disturbances previously discussed. The kilowatt power serves as the primary control input for any microwave extraction process. The evaporation rate of water can be adjusted by increasing the KW power of the microwave magnetron which increases the heating rate of the lunar material. Increasing the exposure time of the material can allow for more water to be evaporated from the material. In the scenario where the targeted material is not heating quickly because of transparency to microwaves, a controlled microwave accelerator can be used to increase the heating rate. Heat accelerators such as carbon magnetite or silicon carbide can be added to the material to increase the heating rate because various metal oxides and carbon have been demonstrated to respond well to microwave heating. The problem of thermal runaway can be countered by mixing or fluidization of the microwaved material (Haque, 1999). The electrolysis phase is largely controlled by the electric current applied to the water (Taylor & Carrier, 1993, 88-90).

Table 12. Consolidated list of Disturbances and Control Variables Microwave Extraction of Polar Permafrost (Haque, 1999).

Disturbances	Control Variables
• Variations in heating rate • Variations in evaporation rate • Variations in particle size • Evaporate contaminates (Colaprete et al., 2010) • Thermal runaway • Variations in temperature • Variations in pressure	• Microwave Power • Microwave Exposure time • Microwave heat accelerator • Mixing/fluidizati on of the lunar polar ice material • Electric current (electrolysis) (Ethridge & Kaukler)

VI.4 Interpreting Each Dimension of Static Complexity

VI.4.1 Capturing Each Element of Static Complexity in Decision Making

Up to this point in the analysis, three separate dimensions of static complexity have been investigated and a mechanism for evaluating each of them in the setting of lunar oxygen production has been proposed. Q-connectivity analysis was suggested as a tool with which to evaluate interconnective complexity. Q-analysis and application of Equation 8 generates a number quantifying the interconnective complexity of the overall system. The application of techniques from Q-connectivity analysis can be expanded to interpret the complexity associated with strength of connections in a lunar oxygen production system. The proposed technique allows an analyst to selectively view the system's interactions based on a defined physical and measureable property between the components. After applying the filtration technique and generating a new structure, that structure can be analyzed to reveal its interconnective complexity. If a single outstanding metric can be identified to best represent the strength of connections between components, the interconnective complexity of the resulting matrix could be used as an alternate complexity measurement. Lastly, a mechanism was proposed with which to evaluate the complexity associated with variety through its ability to translate into variety in behavior. A value is generated through Equation 9 which quantifies variety in behavior. There are effectively three different values generated from the static complexity analysis and the higher values represent higher static complexity in each case.

Each of the analyses can serve as a stand-alone evaluation. That is, a decision maker has the flexibility to select and perform only the analyses that are perceived as useful in the current situation. The obtainable information would then be evaluated as previously discussed for each type of analysis. Each of the analyses provides a completely different perspective of a system's static complexity. Performing each analysis allows the decision maker to identify the sources that contribute the most static complexity for a given system. However, the goal may be to determine which lunar oxygen production process has higher overall static complexity. The literature has not provided a mechanism by which to aggregate each of the separate elements into a comprehensive measurement for static complexity. Thus, the use of a type of decision-making analysis called SMART is proposed as a means to combine each metric.

This difficult decision-making scenario involves multiple attributes, each of which is based on different metrics and are not directly comparable through quantitative means. There is also an inherent cloud of subjectivity that cannot easily be removed. One must ultimately decide which of these attributes is seen to contribute greater static complexity to the system. It is for these types of decision-making scenarios that various forms of Multi-Attribute Utility Analysis (MAUA), also called Multi-Attribute Criteria Analysis, have been proposed. SMART is one of these proposed techniques (Goodwin & Wright, 2004, 15-57).

The most common of such MAUA techniques is called the Analytical Hierarchy Process (AHP). This technique was originally proposed as a method to handle scenarios involving multiple objectives and inherent uncertainty. The method involves making pair-wise comparisons between each of the attributes and applies a mathematical procedure using linear algebra applications to generate a solution. This technique generally requires computer software to perform due too the complexity of the calculations involved (Goodwin & Wright, 2004, 413-425). Other such techniques are the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), ELimination Et Choix Traduisant la REalite Method (ELECTRE), Improved COmplex PRoportional ASsesment Method (COPRAS), and Simple Multi-Attribute Rating Technique (SMART). Numerous methods exist, each of which was created for specific types of decision-making applications involving multiple attributes (Rao, 2013 and Goodwin & Wright, 2004, 29–57).

SMART is chosen as a suggested method for static complexity aggregation because of its inherent simplicity. SMART can be used when a more complicated analysis either is not desired or believed to provide the decision maker more transparency about the situation. Thus far, several assumptions have already been made in this analysis of static complexity to make the analysis more manageable. It has been assumed that static complexity can be captured through three different types of dimensions, and in each analysis and in each case, assumptions have been made to simplify the problem. Due to the assumptions and simplifications implemented within the static complexity analysis, it is not likely that a more complex decision-making analysis will provide greater understanding of the problem. What is more helpful is a simple and manageable analysis that, at the very least, provides the decision maker an increased understanding of the problem. The simplicity of SMART commends it as a practical way to aggregate the static complexity from each analysis.

VI.4.2 Application of the SMART Technique for Determination of Overall Static Complexity in Lunar Oxygen Production

Before explaining the application of SMART, several terms are clarified. An objective is the "...preferred direction of movement" (Goodwin & Wright, 2004, 28). In this analysis, the preferred direction of movement is to minimize static complexity. An alternative is a course of action that can be taken. An attribute is a property used to measure the performance of each alternative in relation to an objective. A value is a numerical score for the performance of an attribute in relation to an objective. The value for each attribute is also referred to as the utility for that attribute. For the application of SMART, values for each attribute are assumed to not involve risk or uncertainty (Goodwin & Wright, 2004, 28–29).

SMART can be applied to a given decision-making scenario assuming the below axioms are satisfied. Each axiom assumes that the decision maker is behaving rationally and can accept the preference ranking indicated by the method (Goodwin & Wright, 2004, 49).

- Decidability: It is assumed that the decision maker can decide which attributes and alternatives are preferred.
- Transitivity: If a decision maker prefers arbitrary option A over B and prefers arbitrary option B over C, then the decision maker must prefer option A over C.
- Summation: If a decision maker prefers A over B and B over C, then the strength of preference of A over C must be greater than the strength of preference of A over B.
- Solvability: Assumes that the decision maker can identify a clear halfway point between the range of values for each alternative. This is necessary for the application of the bisectioning technique explained in this section.
- Finite upper and lower bounds for value: Assumes that there is a lower and upper bound for the values returned by each alternative.

The main steps in SMART are summarized below (Goodwin & Wright, 2004, 30–31):

- Identify the decision maker.
- Identify the alternative courses of actions.
- Identify attributes which are relevant to the decision making problem;
- For each attribute, assign values to measure the performance of alternatives on that attribute.
- Determine a weight for each attribute.
- For each attribute, take a weighted average of the values assigned to that alternative.
- Make a provisional decision.
- Perform a sensitivity analysis.

The application of SMART is explained using the objective, alternatives, and attributes relevant to this study. For this study, the decision maker is assumed to be some future analyst evaluating alternative lunar oxygen production processes when the state of research has matured. The objective is ultimately to identify a lunar oxygen production process that has the least static complexity. In this study there are four alternative processes available: hydrogen reduction of ilmenite, carbothermal reduction, molten silicate electrolysis, and microwave extraction of polar permafrost. There are three possible attributes in which to measure the performance of each alternative process relative to the objective. These possible attributes are: interconnective complexity, interconnective complexity with a strength of connections analysis applied, and variety in behavior. Each attribute has numerical values by which performance is evaluated.

Because of the limitations in knowledge regarding lunar oxygen processes, each dimension of static complexity could be taken only so far with respect to generating real data. All three dimensions are too limited to generate authentic and reliable data. Thus, notional data are envisioned for each type of static complexity and used for demonstration. The alternatives, perspective attributes, and notional data values are collected in Table 13.

Table 13: Lunar Oxygen Production Process and the Notional Performance Data for Each Attribute.

Lunar Oxygen Production Process	Interconnective Complexity	Interconnective Complexity (strength of connections)	Variety in Behavior
Hydrogen Reduction of Ilmenite	2.4	1.2	1.4
Carbothermal Reduction	3.7	3.2	1.3
Molten Silicate Electrolysis	2.2	1.7	1.1
Microwave Extraction of Polar Permafrost	1.3	1.3	1.9

The notional interconnective complexity values would be generated through Equation 8 presented in section V1.1.1. To note, the interconnective complexity values previously generated in Table 8 did not demonstrate great differentiation in complexity. Thus, using notional values for interconnective complexity with greater differentiation allows for a more effective demonstration of the SMART technique. The notional variety in behavior ratios would generated through Equation 9 in section V1.3.2. Although the values for each separate attribute may look somewhat similar, the numbers represented cannot be directly compared as they are currently presented. Each of these values must be converted into a form such that they can be compared. Also, the perceived contribution of each attribute must be considered. SMART provides a simple way to convert all values to a similar scale (SMART scale) represented by a range of 0 to 100. (Goodwin & Wright, 2004, 29–57).

To convert the data presented in Table 13 to a SMART scale, the technique makes use of value functions. A value function is a mathematical function that describes the relative strength of preference for a particular alternative with respect to an attribute. The first step in creating a value function is identifying the endpoint data values that directly correspond to values 0 and 100 in the SMART scale. The endpoints do not necessarily have to be the highest or lowest values present in the data. For each attribute, endpoints are selected arbitrarily and shown in Table 14 below. The next step in creating a value function is to identify a halfway point in the data for each attribute. The halfway point represents the perceived value in the data range where improvements gained or lost are identical below and above the halfway point. This halfway point does not necessarily have to be halfway in the range of values. Second, the same process is repeated for the two midpoints between the halfway point and the bottom and top of the range. Halfway points and midpoints are selected arbitrarily for each attribute and shown below in Table 14. (Goodwin & Wright, 2004, 37–39).

Table 14: Lunar Oxygen Production Process and the Notional Performance Data for Each Attribute.

Attribute	V(0)	V(25)	V(50)	V(75)	V(100)
Interconnective Complexity	1.0	2.0	3.0	4.0	5.0
Interconnective Complexity(strength of connections applied)	1.0	1.7	2.0	3.3	4.0
Variety in Behavior	1.0	1.3	1.5	1.9	2.5

The purpose of a value function is to estimate the values of any attribute to a value in the SMART scale of 0–100. Using simple curve-fitting functions of Microsoft Excel, a trendline and corresponding equation are generated for each attribute as shown in Figures 38 through 40. Thereafter, Table 15 summarizes the approximate value functions.

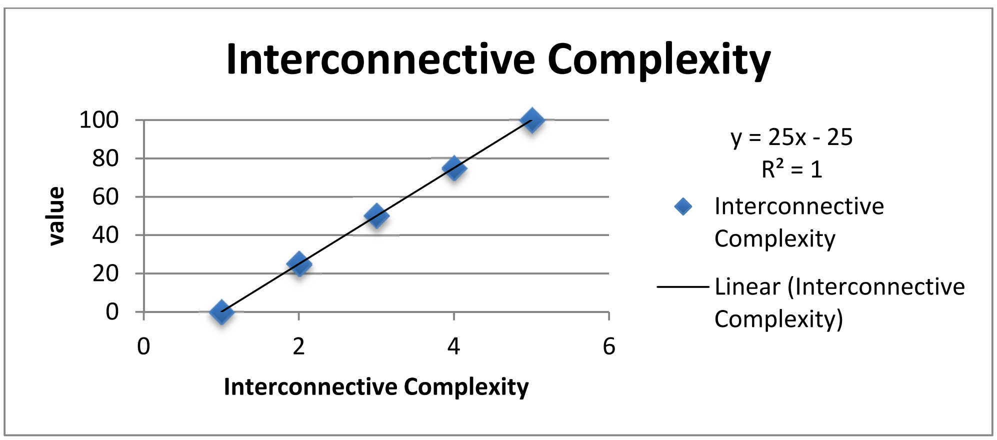

Figure 38: Value Function for Interconnective Complexity.

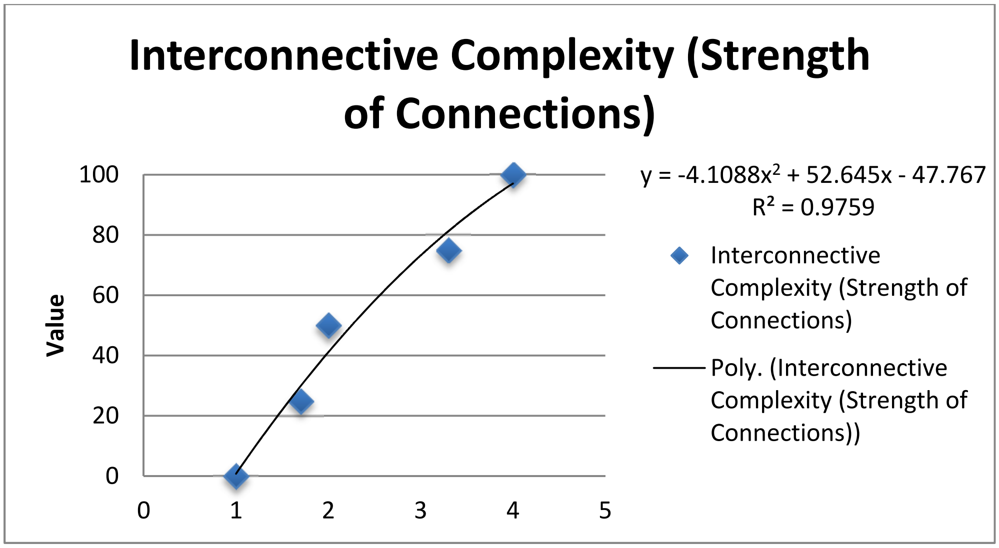

Figure 39: Value Function for Interconnective Complexity (Strength of Connections).

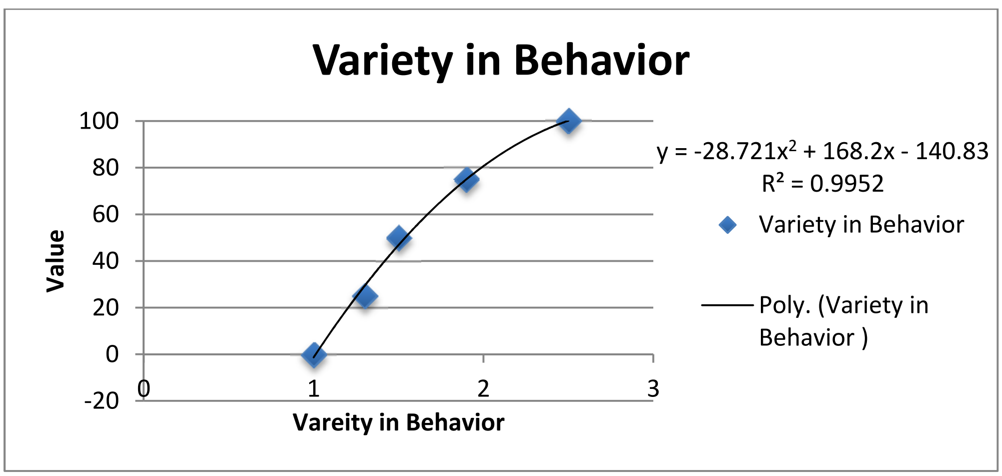

Figure 40: Value Function for Variety in Behavior.

Table 15. Lunar Oxygen Production Attributes and Value Functions.

Attribute	Approximate Value Function
Interconnective Complexity	Y = 25x - 25
Interconnective Complexity Strength of Connections	Y = -4.1x2 + 52.6x - 47.8
Variety in Behavior	Y = -28.8x2 + 168.2x - 140.8

The value function effectively allows the analyst to place each attribute on the SMART scale. However, for a decision to be made, values must be combined from different attributes. This combination must also reflect the decision maker's preferences toward each attribute with regard to what is viewed as more or less concerning to the given problem. SMART deals with preference by attaching weights to each of the attributes. Specifically, SMART makes use of a swing weight technique.

At a simplistic level, one could imagine simply identifying how many times more important one attribute is to another. As an example, it may be possible that a decision maker identifies interconnective complexity as contributing three times more static complexity than variety in behavior. This type of weight is referred to as an ***importance weight***. Goodwin and Wright (2004) comment about problems associated with importance weights. Importance weights "...do not take into account the range between the least and most preferred options on each attribute. If the options perform similarly on each attribute, so that the range between best to worst is small, this attribute is unlikely to be important, even though the decision maker may consider it to be an important attribute per se" (Goodwin & Wright, 2004, 40). If the other extreme is taken, a weight attached to an option could be zero because it has no importance in deciding between various alternatives. These issues can be surpassed by making use of swing weights, which allows the decision maker to "...compare a change (or swing) from the least-preferred to the most preferred value on each attribute to a similar change in another attribute" (Goodwin & Wright, 2004, 40–41).

The process of applying swing weights to an attribute is performed in two steps: swing weights are created and normalized weights are derived from the original swing weights. The normalized swing weights are used in making the final decision. To create a swing weight, the decision maker identifies which attribute is viewed as the most important to the decision at hand. In this analysis, the question is: which attribute contributes the most to the overall static complexity in a lunar oxygen production process? Next, the decision maker determines the importance of each of the other attributes as a function of percentage to the attribute identified as the most significant. This procedure is shown under the original swing weight column of Table 16. Arbitrary swing weights are chosen for demonstration purposes. Interconnective complexity is assumed to contribute the greatest contribution to static complexity. Variety in behavior is assumed to contribute 70% of interconnective complexity. The interconnective complexity associated with the strength of connections analysis is assumed to contribute 20% as much to static complexity as does interconnective complexity without addressing strength of connections.

After the swing weights have been created, they are then normalized to the SMART scale of 100. To normalize the swing weights, each original swing weight is divided by the sum of all the swing weights and multiplied by 100. Each value is rounded to the nearest whole number for simplicity. As a result of the rounding, the sum of the normalized weights is 101 which is approximately 100 (Goodwin & Wright, 2004, 41–43).

Table 16: Lunar Oxygen Production Attributes and Swing Weights

Attribute	**Original Swing Weight**	**Normalized Swing Weight (Nearest Whole Number)**
Interconnective Complexity	100	53
Interconnective Complexity (Strength of Connections)	20	11
Variety in Behavior	70	37
Sum	190	101

The value functions created earlier allow the decision maker to translate the performance of each attribute to the SMART scale. The applied swing weights allow the analyst to compare the overall contribution of each attribute in relation to the objective. The complexity associated with each alternative can now be aggregated. Goodwin and Wright (2004) apply what is referred to as the additive model for aggregation. The additive model involves two steps. First, it measures how each alternative performs on each attribute. Second, it uses the swing weights to compare the values allocated with one attribute to values allocated to another attribute (Goodwin & Wright, 2004, 43–44). A calculation for each lunar oxygen production process is performed and is shown below as Tables 17 through 20.

The original values for each attribute from Table 13 are converted into comparable values through application of the value functions summarized in Table 15. This conversion can be done through estimation by application of the curve fitting shown in Figures 38–40. The conversion can also be done by direct calculation using the value functions in Table 15. For the below calculations, the value functions were used to calculate the new SMART values for each attribute. Following Tables 17-20, the aggregate complexity is summarized for each process in Table 21.

Table 17. Hydrogen Reduction of Ilmenite Aggregate Notional Static Complexity.

Attribute	Hydrogen Reduction of Ilmenite Values (Generated from Value Functions)	Weight	Value X Weight
Interconnective Complexity	35	53	1855
Interconnective Complexity (Strength of Connections)	9.416	11	103.576
Variety in Behavior	38.232	37	1414.58
Sum			3373.16

Table 18. Carbothermal Reduction Aggregate Notional Static Complexity.

Attribute	**Carbothermal Reduction Values (Generated from Value Functions)**	**Weight**	**Value X Weight**
Interconnective Complexity	67.5	53	3577.5
Interconnective Complexity (Strength of Connections)	78.536	11	863.896
Variety in Behavior	29.188	37	1079.96
Sum			5521.35

Table 19. Molten Silicate Electrolysis Aggregate Notional Static Complexity.

Attribute	**Molten Silicate Electrolysis Values (Generated from Value Functions)**	**Weight**	**Value X Weight**
Interconnective Complexity	30	53	1590
Interconnective Complexity (Strength of Connections)	29.771	11	327.481
Variety in Behavior	9.372	37	346.764
Sum			2264.25

Table 20. Microwave Extraction of Polar Permafrost Aggregate Notional Static Complexity.

Attribute	**Microwave Extraction of Polar Permafrost Values (Generated from Value Functions)**	**Weight**	**Value X Weight**
Interconnective Complexity	7.5	53	397.5
Interconnective Complexity (Strength of Connections)	13.651	11	150.161
Variety in Behavior	74.812	37	2768.04
Sum			3315.71

Table 21. Summary of Notional Aggregate Static Complexity for Each Process.

Lunar Oxygen Production Process	Aggregate Static Complexity
Hydrogen Reduction of Ilmenite	3373.16
Carbothermal Reduction	5521.35
Molten Silicate Electrolysis	2264.25
Microwave Extraction of Polar Permafrost	3315.71

The notional aggregation results reveal that molten silicate electrolysis has the lowest static complexity of the four processes. Since the objective was to minimize static complexity, molten silicate electrolysis is the most desirable from the standpoint of static complexity. Conversely, carbothermal reduction has the highest static complexity of any of the processes and is the least desirable from the standpoint of static complexity. Hydrogen reduction of ilmenite and microwave extraction of polar permafrost have roughly equal static complexity values.

The last step in the application of the SMART technique is to perform a sensitivity analysis. A sensitivity analysis evaluates how robust the selection of an alternative is to parameters used in the analysis. There may be several parameters that could be significantly adjusted and the resulting aggregation would not change the selection of an alternative. Likewise, small adjustments to a parameter could change the outcome of the analysis. In that case, extra caution must be placed on the confidence in the determination of that parameter. Performing the sensitivity analysis should give the decision maker a greater understanding of the problem by increasing his understanding of what parameters are of the greatest significance (Goodwin &Wright, 2004, 47–48).

Through investigating the data for interconnective complexity (strength of connections), it is readily apparent that it has a comparatively small contribution on the outcome because its weight is significantly smaller than the other attributes. As a result, small changes in its relative weight will have little effect on the analysis. For interconnective complexity (strength of connections) to have more influence, its normalized weight would need to be more comparable to the other attributes. The Value X Weight columns of Tables 17–20 reveal that interconnective complexity (strength of connections) is consistently substantially smaller than the largest value in that column.

However, because variety in behavior is weighted as 70% as important as interconnective complexity, the outcome is more sensitive to smaller changes in variety in behavior data and the selection of weights. To demonstrate, the data for microwave extraction of polar permafrost (Table 20) reveals that the majority of its complexity is derived from variety in behavior. A moderate reduction in the normalized weight (15–20%) for variety in behavior could easily adjust the outcome so that microwave extraction of polar permafrost has the lowest static complexity or a comparable static complexity to molten silicate electrolysis. This result occurs because microwave extraction of polar permafrost scores low on both interconnective complexity and interconnective complexity (strength of connections). Thus, the decision maker should take extra caution to confirm that variety in behavior is 70% as important as interconnective complexity.

The outcomes generated in this analysis are purely hypothetical and cannot been taken to indicate the actual static complexity of each of the studied processes. It would have been desired to use more authentic data, but unfortunately the development of lunar oxygen production is too premature to generate such data. Nonetheless, this notional analysis demonstrates that the SMART technique may serve as an effective method to aggregate the results from each dimension of static complexity. The simplicity of the technique is desired because too many assumptions and simplifications have already been made to justify a more complex decision-making analysis.

CHAPTER VII

CONCLUSIONS

The intent of this thesis is to develop a foundational framework for static complexity analysis in lunar oxygen production systems which sets a baseline for a more complete analysis when these processes are no longer notional systems. Static complexity, part of a larger framework for system complexity, measures the complexity associated with the steady state topology of a system. Static complexity is simplified and made manageable by focusing on the most important elements contributing to static complexity, which are: hierarchical structure, interconnective complexity, strength of connections, and complexity in variety. For the context of this study, static complexity is defined as the overall contribution from complexity associated with each of these elements. Hierarchical structure was not evaluated because information would be needed about the overarching organizational body responsible for executing decisions on the lunar base, which is not currently known at this time.

A set of methods are proposed upon which to evaluate each dimension of static complexity. In each case, the methodology is explained and demonstrated using current notional information about lunar oxygen production systems. Q-connectivity analysis is suggested as a tool with which to evaluate interconnective complexity of a lunar oxygen production process. The application of Q-connectivity analysis is then expanded with the use of a weighted relationship and a filtration technique to determine the complexity associated with strength of connections. A mechanism is then proposed in which to evaluate the complexity associated with variety through its ability to translate into variety in behavior. This translation is performed using the law of requisite variety from cybernetic theory. Lastly, because the ultimate goal is likely to decide which system has greater static complexity, the decision making technique SMART is suggested as a potential means to aggregate the results and create a holistic measurement for static complexity.

In the interconnective complexity analysis, process diagrams are created to represent the interactions of components for four lunar oxygen production processes studied in this thesis. Thereafter, the component interactions are studied using Q-connectivity analysis. The analysis reveals that carbothermal reduction has the highest interconnective complexity because it has more disconnected sets of higher dimensional interactions. Each of the other processes resulted in a complexity of 1. This result is an artifact of the level of detail inherent in the process diagrams. In the strength of connections analysis, a weighted relation and the filtration technique is applied to a hypothetical process featuring large temperature and pressure variations. The analysis demonstrates that changing the parameters in the filtration technique produces different structures with varying complexity. It was then concluded that the parameters of the filtration technique should represent physical limitations or properties of the system.

Next, it is demonstrated that the law of requisite variety from cybernetic theory can be used to determine complexity associated with variety in behavior, which identifies the ratio in control forces and disturbances. Because it is impossible to identify every potential disturbance and control force that will exist in future lunar oxygen production systems, many of the known disturbances and control forces are consolidated using known information about the notional lunar oxygen production process and analogous terrestrial systems. Lastly, hypothetical complexity data are created for each of the four processes studied and the SMART technique is demonstrated by aggregating the hypothetical complexity data. In applying these various techniques, a foundational framework was developed to evaluate static complexity in lunar oxygen production systems.

CHAPTER VIII

RECOMMENDATIONS

A few general recommendations are made to improve the quality of the static complexity analysis presented in this study and overall system complexity analysis. First, because the focus of this study is on static complexity, the other essential complexity element, dynamic complexity, was not considered. The proposed static complexity framework should be used simultaneously with an analysis of the dynamic complexity of the various lunar oxygen production processes. Q-connectivity analysis also presents tools that could be used to interpret the dynamic complexity for lunar oxygen production processes. Traditional methods for dynamic considerations typically involve functional relationships. Approaches include time series models, space-time extensions, and nonlinear or differential equations. However, Q-connectivity analysis provides a different view. Q-analysis can be used to handle two categories of change which include changes to the vertices or simplices of the data matrix representing a system's structure, and changes to the behaviors that exist in the multidimensional space on which components interact. Refer to Gatrell and Beaumont (1982) for an expansion of these concepts. Future works that expand upon the proposed static complexity framework should investigate the contribution of dynamic complexity to overall system complexity, and Q-analysis could be used to interpret several aspects of dynamic complexity.

Future considerations should also include the hierarchical structure element of static complexity. Because a method to determine the hierarchical structure of a lunar oxygen production system was not discovered, future work should develop such a technique. The method should ideally include human and computerized elements associated with the system's hierarchical structure. Considering interconnective complexity, there is need for engineers to develop more detailed process diagrams for each of the processes under considerations. Because of the limitations in detail in the currently available process diagrams presented in this study, the results did not fully demonstrate differences in interconnective complexity for each process. Improved detail within each of the process diagrams would allow for greater transparency of each system's true interconnective complexity. For strength of connections, future engineers should consider which metric, if one exists, is ideal for determining strength of connections, when more knowledge about these systems is known. Lastly, future engineers should continue to expand upon the disturbances and control forces that influence variety in behavior as more knowledge progresses.

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