A PRODUCTION CAPACITY INVESTMENT DECISION-MAKING TOOL FOR THE INDOOR VERTICAL FARMING INDUSTRY

by

Benjamin Schulman

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ABSTRACT

Indoor vertical farming (VF) systems are a form of controlled environment agriculture, making use of modern technology to improve food availability and security. Commercially, it is a young industry set to disrupt the food supply chain status quo but is faced with a uncertainty and risk with respect to product demand and production technology efficacy. Currently funded largely by private investment, VF firms are challenged with properly developing production capacity for long-term profitability. This research presents a method developed for VF firms to facilitate decision making associated with allocation of capital resources to new production capacity considering demand and production uncertainty. The method makes use of two sequential MILP formulations to develop production capacity plans and presents an evaluation said plans performance. The method is extended to provide the expected value of perfect information associated with reducing this uncertainty and suggests that something equivalent 3% and 4.5% of a new production facility's capital cost should be spent on research and development associated with production technology efficacy and demand respectively. The author's experience with GoodLeaf Farms, a Nova Scotia-based indoor VF company, was used as a basis for developing the method and a theoretical case study to prove its function.

List of Abbreviations and Symbols

AHU	Air Handling Unit
CEA	Controlled Environment Agriculture
DLI	Daily Light Integral
DSn	Demand Scenario n
DSS	Decision Support System
EPPI	Expected Profit of Perfect Information
EVPI	Expected Value of Perfect Information
EVPI	Expected Value of Perfect Information
FIFO	First-In-First-Out
IF	Interaction Factor
LED	Light Emitting Diode
LF	Lighting Factor
LGV	Leafy Green Vegetable
M1	Model 1
M2	Model 2
MILP	Mixed Integer Linear Program
PAR	Photosynthetically Active Radiation
PFAL	Plant Factory with Artificial Lighting
PPFD	Photosynthetic Photon Flux Density
PUO	Perfect Unit Output
RF	Irrigation Recipe Factor
SKU	Stock Keeping Unit
TA	Traditional Agriculture
TEP	Total Expected Profit
TTN0	Time To Net-0
VF	Vertical Farming

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1. INTRODUCTION

1.1. VERTICAL FARMING AND CONTROLLED ENVIRONMENT AGRICULTURE

As the global population continues to grow, surpassing eight billion people, the increasing need to provide affordable, nutritious food is pushing the agricultural industry to greatly improve its efficiency and efficacy. Spurred on by climate change, urbanization, and soil degradation and depletion, arable land per person is forecast to decrease significantly in the coming years, mounting serious pressure on the global food supply chain associated with traditional agriculture (TA) (Benke & Tompkins, 2017). Projections suggest that by 2050, the population of Earth will require upwards of 70% more food than produced in 2013 (Mitchell, 2022). Vertical farming (VF), a recent development in controlled environment agriculture (CEA), represents a suite of agricultural technology and methods that may help solve these issues as well as enhance the production and quality of many different crops (van Delden et al., 2021).

Throughout history, technological improvements, such as animal husbandry, irrigation systems, internal combustion engines, and mechanized tractors, crop breeding, and pesticides, have marked significant gains in the efficiency of agricultural practices. CEA refers to a set of horticultural and engineering techniques and methods used to control and optimize crop yield, quality, and efficiency by controlling growing parameters. To facilitate this level of control, most CEA operations are indoor operations – plant factories, container farms, greenhouses, and vertical farms – making use of technology to fine-tune horticultural inputs and variables – light parameters like spectrum and intensity, environmental conditions, and irrigation recipes. Though there is some evidence of CEA dating back to the Roman Empire, and control over outdoor crop irrigation has existed for over 12,000 years, greenhouses, dating back as far as 30 CE, are typically regarded as the original CEA system (Cornell CALS, 2022). Allowing year-round production of foodstuffs and ornamentals, they are still in use today, albeit in a more developed capacity. It was not until 1949 with the first phytotron, an indoor controlled environment grow chamber, that research into understanding optimal growing conditions, and the potential promise of VF systems, started to shift into focus. Largely centered on academic applications, phytotron technology continued to develop across the globe for subsequent years, and highly controlled research phytotrons are still used in academia today. The typical level of technology and control applied to these systems are economically inviable for commercial use (Mitchell, 2022).

Initial commercial applications of completely indoor CEA technology date back to the seventies, with organizations like Geniponics or Phytofarms, but ultimately would fail as a result of cash-flow challenges due to the high cost of the required technology and electricity, due largely to the use of artificial lighting, to operate these types of facilities. Japan is largely viewed as a pioneer in the commercial indoor CEA space, with facilities operating since the 90s, though their true commercial viability is questionable as they rely heavily on government and academic subsidy to continue operation. The development of light emitting diodes (LEDs), their associated improved efficiency and continual cost reductions, and the development of the cannabis industry in North America, one which typically uses indoor CEA techniques to create a high-value product, has led to an increase in interest in, and potential viability of, the commercial food-producing VF industry (Mitchel, 2022).

Presently, a VF system is typically defined as a CEA system, making use of a hydroponic nutrient delivery system, artificial lighting (typically facilitated by LED light modules), and a controlled environment, with multi-layer indoor crop production structures. This multi-layer characteristic allows for the principal benefit of large-scale indoor VF system food production – these facilities can be located very close to major population centres, allowing for more efficient land use, and significantly decreased transportation costs when compared to TA methods. Further, the level of control afforded by modern VF systems provides the opportunity for a much-increased level of production and manufacturing optimization when compared to TA. VF systems typically allow for control over many environmental variables that determine plant behaviour – light (intensity, spectrum, etc.), irrigation (nutrient availability, feed rate, etc.), and climate (air temperature, humidity, etc.) - allowing for more predictable plant growth and targeted expression in specific crops. At the time of this publication, indoor VF systems used for commercial food production are largely focused on growing leafy green vegetables (LGVs). Though other crops are technically possible, due to their relatively short growth cycles per yielded mass, LGVs are considered the proving grounds for the commercial viability of the industry.

Though there has been significant investment over the past 5-10 years in the indoor VF food production industry, the large capital, operational expenses, and risk profile associated with these systems continues to garner some skepticism as to the financial viability of the industry. As outlined by Peterson and de Souza (Controlled Environment Plant Physiology and Technology, 2019), firms operating in emerging industries are implementing business plans that are typically unproven amidst market size and growth projections that are highly speculative. This has created a highly competitive landscape with limited collaboration and knowledge sharing as VF firms race to perfect their operational models and strategies. Determining and properly evaluating a viable high-level strategy is proving challenging for the industry - firms should focus on either being cost leaders, product leaders, or specialization leaders, but typically are simultaneously focusing on two or three of these (Peterson & de Souza, 2019). Maintaining sole focus on a given strategy under pressure from investors and competitors in an industry lacking collaboration, standardized data, and processes is difficult. Further, this lack of industry standards with respect to processes, control, data collection and monitoring, has led to a very limited amount of peer-reviewed literature evaluating the true economics and financial viability of the VF food production industry – it's difficult to research something that is a) not executed in a generalized way, and b) not openly discussed (Baumont De Oliveira et al., 2022). The lack of industry collaboration and economic literature creates a need for uncertainty-based decision-making tools like the one proposed in this thesis. Such tools should help VF firms, like GoodLeaf Farms, in allocating capital to operational expansion projects optimally against differing business goals – maximizing long-term profit, investment payback period, operational robustness to uncertainty, etc.

1.2. GOODLEAF

This section gives a brief outline of the history and current state of GoodLeaf Farms, a VF firm and producer of LGVs, experience with which the author has used as a basis for the development of this research.

1.2.1. HISTORY

GoodLeaf Farms began in 2011 in Bible Hill, Nova Scotia as a proof of concept that hydroponically grown food has a place in the future of the food supply chain in Canada. For the first 4 years of its existence, GoodLeaf and its small team operated a small-scall vertical farm, focused on research and development. This allowed them to select varieties and products that are both market viable and production feasible. They were also able to develop their CEA know-how and techniques and, at a small scale, test local commercial markets. Though originally open-ended, GoodLeaf's focus quickly centered on LGVs, specifically baby greens and micro greens.

In 2015, GoodLeaf started its first commercially producing VF facility in Bible Hill. The facility was retrofit into an old elementary school, using the gymnasium as the grow chamber[1]. The operation consisted of the six main components of a CEA/VF process: seeding, germination, growing, harvesting, packaging, and cleaning. The annual production capacity of the Bible Hill farm was approximately 28,000 kgs of LGVs and offered up to eight different products. The principal production systems used in this farm were relatively simple. Single-source lighting from LED light fixtures with a single, static, Red, Blue, and Far-Red spectrum was used throughout. A Deep-Water Culture with floating tray irrigation system was used where the entire grow chamber was supplied by a single nutrient recipe[2]. Climate control was managed centrally, with CO_2 supplementation, via aisle-located air duct-socks and a single floor-level return. The operation relied heavily on manual labour with operators seeding by hand, often harvesting by hand with scissors, and manually managed material handling throughout the process (e.g., using scissor lifts

[1] The grow chamber is the room in which product is grown.
[2] More details on lighting systems, nutrients and irrigation systems can be found in section 2.1

to add/remove growing product to the grow chamber). Though this operation was a commercial success in as much as proving a viable market for the products it produced, selling into Nova Scotia and Newfoundland and Labrador grocery stores, the level of labour required for the operation made profitability a challenge.

Based on the success and continued operation of the Bible Hill Farm, GoodLeaf was able to successfully secure a significant round of funding in early 2017 to build a much larger, much more automated VF facility in the Greater Toronto Area. Construction began in Guelph, Ontario in late 2017, with production beginning in late 2018. Since late 2019 the Guelph farm has been operating at or close to its production capacity of approximately 350,000 kgs of LGV per year, selling products into national retail chains (e.g., Loblaws, Metro, etc.) and food service companies (e.g., Gordon Food Service, Sysco, etc.).

1.2.2. Future Expansion and Standardization

Since the start-up of the Guelph farm, GoodLeaf has brought on further investment and partnership from McCain Foods and begun design and preliminary construction work on still larger (approximately 900,000 kgs of LGV per year) VF systems in the Montreal and Calgary areas. Beyond these two new facilities, GoodLeaf plans to expand rapidly, over the next 4-6 years, with new production facilities across Canada and the United States. In the interest of moving quickly, and enterprise-level efficiency and coherence, these new facilities will be heavily influenced by, and generally standardize the theory of, operational and system design in the Guelph farm.

GoodLeaf's standard facility leverages automation and a passive first-in-first-out (FIFO) grow chamber to significantly reduce the total labour per unit output as compared with their Bible Hill facility. Crops are grown in industry-standard open (not celled) trays measuring approximately 25cm x 50cm. Once seeded, these trays are placed into industry-standard mobile ebb and flood tables. The mobile tables are typically around 2m long and can range in width between 2m and 7.5m. They are made of an aluminum frame with a plastic tray insert to facilitate irrigation events. The mobile tables have two sets of casters on their underside to allow for movement on a set of rails in the short-edge direction of the table.

Figure 1. Typical mobile ebb and flood table

A brief and generic description of the six operational processes and how they are managed in GoodLeaf's "standard" VF follow:

1.2.2.1. *Seeding*. Trays are filled with growing media (substrate) and seeds according to the specified density and distribution requirements for the variety to be grown. Seeding system costs and throughput rate can vary depending on level of automation sourced. Once seeded, trays are loaded into mobile tables

1.2.2.2. *Germination*. The germination space is kept dark and humid to facilitate the initial stages of plant growth. Fully loaded mobile tables are transferred into the germination space where they are held for a short period - exact germination time is variety dependent.

1.2.2.3. *Grow*. Once germinated, tables are transferred to the "load-in" end of the grow chamber. The grow chamber has a series of racking structures, known as stacks, which run the length of the grow chamber from "load-in" to "unload". Each stack has several vertically spaced growing surfaces, known as layers, and each layer has several table positions. Tables are lifted to a specific layer in a specific stack via automation and pushed into the first table position for that layer on a set of table transfer rails. In so doing, the newly added table pushes into the table already in that position moving it into the next position along the length of the layer. This creates a passive-movement FIFO system of tables in each layer. Tables are pulled off the unload end by automation, brought to floor-level and moved out of the grow chamber for harvesting. Plants can be grown in layer-sized batches where an entire layer's worth of tables are loaded in at a time, stay there for the duration of the plant's post-germination grow cycle (variety-specific), and then removed (by adding another batch), or can be grown in smaller batch sizes and move along the length of the layer over the course of the plant's post-germination grow cycle.

- Single-source lighting is facilitated using lightbar modules with an array of LED diodes. Light modules are mounted on the underside of a layer's racking structure to provide light to the layer that is underneath. Lighting systems can be designed to produce different spectra according to product requirements, or a flexible control technology to change spectra as needed (discussed further in Section 2.1.1). Lighting can also be dimmed and turned completely off to facilitate the proper daily light integral (DLI). For a given facility, lighting control zones can be sized to any grouping of tables or layers (e.g., control lighting output for an entire layer, half a layer, multiple layers).
- Irrigation is executed using an ebb and flood system (further explanation of irrigation systems in Section 2.1.2). Each table location along a layer has a flood tap and a drainage trough. Tables are flooded periodically for a specified duration and gravity-drain through a drainage port in their plastic liner to the drain trough. Drained nutrient feed is captured, treated, and recirculated. A given facility can manage a variety of different nutrient recipes according to what is required for the plants being produced by that facility. Nutrient recipes are managed via precision dosing concentrated

nutrients into large recipe delivery tanks. For a given facility, irrigation delivery zones can be sized to any grouping of tables or layers (e.g., flood an entire layer, half a layer, multiple layers). Any grouping can be connected to any combination of available nutrient recipes (at cost).

- Climate control is facilitated with a set of large air handling units (AHUs) which manage the temperature and relative humidity in the grow chamber to a given setpoint. The entire climate is managed as one and kept as uniform as possible in all locations within the grow chamber. Fresh conditioned air is distributed as evenly as possible using a sophisticated air delivery manifold and returned similarly. The air is augmented with additional $C0_2$ at the delivery manifold to a given setpoint.

1.2.2.4. *HARVESTING*. Once fully grown, mobile tables of product are removed from the grow chamber and brought into a harvesting area. Trays are removed from the tables and fed through a harvesting system which remove the grown, commercially viable, product from the trays, roots, and substrate. Product is moved to the packaging area. Trays, with waste material, and tables are moved to the cleaning area.

1.2.2.5. *PACKAGING*. Coming from the harvesting operation, product is rapidly cooled and dried. It is then packaged and sold as several distinct products and SKUs according to commercial need.

1.2.2.6. *CLEANING*. Coming from the harvesting operation, waste material - substrate, root mass, left-over vegetation - is removed from trays. Both trays and tables are washed, sanitized, dried, and brought back to the seeding process for reuse.

1.3. PROBLEM STATEMENT

When approaching the design and construction of a new VF operation, firms like GoodLeaf must consider what size of facility to build and what level of production precision, with respect to control granularity (e.g., control growing temperature to the nearest 0.1 degree

C, nearest 1 degree C, etc.), and flexibility they plan to incorporate across the main horticultural and operational systems. Determining this direction is complex due to market uncertainty and currently, is specifically complex for the primary horticultural systems – lighting, irrigation, and climate control – due to the uncertain throughput effect associated with these systems on product yield and quality. Though these types of horticultural production systems allow for a much higher level of control as compared to traditional agricultural methods, the different system combinations and their exact effect on distinct products is highly uncertain. As commercial food-producing VFs do not yet have proven financial viability, more information and insight when considering new facility construction is critically important. Through this research, a method has been developed to facilitate setting this direction. Using a generalized version of the situation with GoodLeaf as a basis for development, this method makes use of two sequential mixed integer linear programming (MILP) models optimizing for total, long-term profit, to determine a set of potential production capacity plans. These plans are then evaluated against a set of criteria (maximum profit opportunity, minimum regret, etc.) to provide decision makers with further insight. This method can also provide a measure of the expected value of perfect information (EVPI) for reducing both market and production effectiveness uncertainty so organizations like GoodLeaf can understand how much of an investment is worth making to reduce these uncertainties via research and development effort such as market/demand forecasting or horticultural experimentation.

2. BACKGROUND/LITERATURE REVIEW

This section reviews works, and details related to the topic of this thesis. It covers CEA production technologies and their associated effects, flexible production capacity and associated planning, and CEA facility design optimization.

2.1. CEA PRODUCTION TECHNOLOGIES.

Large scale food production using CEA or VF systems is a nascent industry and as such there is limited literature on the topic. Centered on the Japanese experience with CEA, Kozai (2018, 2019, 2021) present an in-depth view of the current state of the relevant technologies – so called, Plant Factories with Artificial Lighting (PFALs). These collections outline the technology, principally, the state of current PFALs, industry and business developments, and technological advancements to be implemented in future CEA operations. Specific to this research, further articles discuss the developments in key CEA production technologies; lighting techniques and systems and nutrient solution (irrigation recipe) control to effect plant growth and morphology.

2.1.1. LIGHTING

Light is a key driver in plant growth and development, acting as both a source of energy and as an environmental signal. Photosynthesis, the process by which plants create energy for themselves, is directly powered by plants using light energy to convert carbon dioxide and water into carbohydrates and oxygen. Plants have several types of photoreceptors, allowing them to perceive different characteristics of light (i.e., spectra, intensity) in combination with other environmental factors (i.e., temperature, humidity) to illicit different responses and developments (e.g., phototropism – directional bending of a plant toward or away from a light source (Lumen Learning, n.d.)). Many different lighting technologies have been used in CEA – high pressure sodium bulbs, fluorescent bulbs, etc. – but the industry has recently centred on LED technology both for single-source and supplemental lighting due to cost, efficiency, and customization. Jishi (2018) provides an excellent overview of the use of LED lights in CEA, associated terminology, and how plants use different parts of the lighting spectra. The photosynthetic rate, the rate by which plants generate carbohydrates and which therefor dictates the growth of plants, is a net result of energy absorbing surfaces on the plant, such as leaves, and the amount of light energy received by the plant. Plants and their photoreceptors absorb the parts of the electromagnetic spectrum, mostly within the visible light spectrum, with wavelengths between 400-700 nm, referred to as photosynthetically active radiation (PAR). PAR can be thought of as the *type* of light that reaches a given plant. PAR within the 400 – 500 nm, 500 – 600 nm, and 600 – 700 nm ranges are referred to as blue light, green light, and red light respectively. Further plants respond to a small amount of light in the 700 – 800 nm range, referred to as far-red light. Plants and their photoreceptors also respond to different *amounts* of light, or photosynthetic photon flux density (PPFD) which, in the case of PFALs, is directly related to the intensity of light emitted from the light source and its distribution to the plant surface. Finally, the day light integral (DLI), is the total number of photosynthetically active photons that reach a specific area (e.g., plant leaf surface) over a 24-hour period. In CEA with single-source lighting, the *photoperiod*, or the amount of time within a 24-hour period in which the lighting system is on, transmitting lights to the plants, is typically used rather than DLI. PAR, PPFD, and DLI are all different variables of a lighting recipe which can be used to affect various aspects of plant growth and total biomass accumulation. Primarily through driving photosynthesis, but also via some key morphological responses; stomatal opening, leaf flattening, shade avoidance, etc.

Wong et al. (2020) provide a review of the relevant experimentation on the effect of different lighting conditions (spectra, intensity) on the growth, phytonutrient, and morphology content of different LGVs. From the extensive experimentation, specifically with lettuces, it is clear that light quality differences can have a marked effect on the outcome of the plants. Due to the breadth of possible experimental parameters, it is difficult to determine optimal lighting recipes. Further, optimality may refer to different plant expressions in different situations. Further still, evidence suggests there are cultivar-specific recipes required to achieve specific results.

More specifically, Naznin et al. (2019) conducted experiments with different light treatments in a controlled environment on lettuce, spinach, kale, basil, and pepper plants. For the same PPFD, air temperature, relative humidity, and photoperiod they study the effect of five different PAR treatments as different combinations of red and blue light. The results of these experiments clearly indicate that different spectral treatments result in distinct responses across the test crops – an indicator of species-specific preferences – across both physical response; plant height, dry mass, leaf development, and chemical responses; chlorophyll, carotenoid and antioxidant capacity. For instance, total plant height was increased under a 100% red treatment for lettuce, kale, and peppers, but not for basil or spinach. Also, total antioxidant capacity was highest for basil and pepper under a 91% red and 9% blue treatment whereas the same was true for lettuce, spinach, and kale under an83% red and 17% blue treatment.

In another study, specifically focused on four different Brassicaceae microgreens, Ying et al. (2020) demonstrates further evidence for species-specific responses to different lighting recipes. For this study, they hold constant values of PPFD (albeit, higher than Naznin et al. (2019)), air temperature and humidity, photoperiod, nutrient feeds, and substrate composition. The randomized block experiment trials 5 different lighting recipes as proportion of blue light, ranging from 5%-30%. The results suggest a specific yield response for cabbage microgreens to different blue light treatment, and no differences for the three other species. However, all species showed some morphological differences (leaf length, area, angle) to different light treatments, further which differed from one another, species-to-species.

2.1.2. IRRIGATION

Niu & Masabni (2022) gives some high-level background on irrigation, or hydroponic, systems used in CEA operations. In a broad sense, two categories of systems emerge – solution culture systems and soilless culture systems. Some specific types of systems are:

> Nutrient film technique (NFT), whereby a thin film of nutrient solution is constantly fed to the plants as they grow, allowing oxygen to dissolve into the solution and exposing plant root-zones to air.
>
> Deep water culture, or floating raft, whereby plants are positioned on rafts, or trays, and floated on top of a pool of nutrient solution. This gives constant exposure of nutrient solution to the root zone as the roots are continuously fully submerged in the solution.

Substrate culture system, typically via ebb and flow style system. Plants are grown in a soilless substrate (perlite, peat moss, rockwool, etc.) and periodically flooded with nutrient solution.

Apart from the specific hydroponic system physical characteristics (substrate, delivery method, etc.), the actual nutrient solution itself, and its chemical makeup can have many different variations. Tsukagoshi &Shinohara (2020). Of the 92 natural elements, 17 have been identified as essential to plant nutrition, divided into two classes – macronutrients, required in relatively large amounts, and micronutrients, required in relatively low amounts. There are nine macronutrients: carbon, oxygen, hydrogen, nitrogen, phosphorus, potassium, calcium, magnesium, and sulfur. There are eight micronutrients: boron, iron, manganese, zinc, copper, molybdenum, chlorine, and nickel. Each are required for proper plant growth and development, and each have their own generalized effect if provided to plants in excess or deficit. In CEA, these nutrients are typically supplied to the plants in ion form via ion-specific nutrient management systems, or pre-prepared nutrient recipes whose concentrations are managed via electrical conductivity (EC) monitoring systems.

The idea that each variety or crop requires its own tailored nutrient solution for optimal growth has existed for some time and has been explored in the literature. Kreij (1995) explores differing nutrient and general fertigation requirements (temperature, oxygen, etc.) for various varieties, in different types of systems (substrates, irrigation type, etc.), and for different stages of life. Similarly, in their instructional text, Jones (2005) details that there can be no prescribed optimal fertigation recipes, as it will be highly situationally dependant, and horticulturalists must learn how to develop fertigation management methods across nutrient composition, substrate, irrigation methods, solution characteristics to achieve specific outcomes. Technically, the optimal nutrient recipe for a specific variety, at a specific stage of life, is that which has the same relative proportions of nutrients as the available uptake[3] ratios for that crop. If these ratios are off, it can lead to specific nutrient depletion, and resultant deficiencies, and accumulation, and resultant toxicities (Savvas &

[3] "uptale" is the ability of a crop to absorb nutrients

Gruda, 2018). More specifically, many studies have been done on specific plant varieties to find optimum fertigation recipes. Radman et al. (2021) test two standard nutrient solutions on nettle crops, optimizing for dry weight yield. Unexpectedly, they found that the weaker of the two solutions, by nutrient concentration, performed much better. Oztekin & Tüzel (2007) explore 4 different recipes with increasing concentrations of nitrogen, potassium, magnesium, and zinc and their effect on yield, physical characteristics, and nutrient consumption of green beans. They found that, generally, yield decreased with increasing nutrient content, that there was no significant difference in physical characteristics across the tested recipes and though the amount of nutrient uptake increased as did available nutrients, the uptake efficiency (uptake/applied) would decrease.

2.2. Flexible Production Capacity

The concept of flexible production or manufacturing capacity has been well defined and researched in the literature. Defined well in Browne et al, (1983), as a "complex of automated material handling devices and numerically controlled machine tools that can simultaneously process medium-sized volumes of a variety of part types", they further define and explore eight distinct types of flexibility a manufacturing process can posses:

1. Machine flexibility: capability to easily produce different parts with the same base machine
2. Process flexibility: capability of producing different parts, using different materials, in different ways
3. Product flexibility: capability of producing a new product, or set of products, using the same production technology quickly and easily
4. Routing flexibility: also known as redundancy, capability of continuing to produce parts pending a machine or process breakdown
5. Volume flexibility: capability of a manufacturing system to operate profitably at different production volumes
6. Expansion flexibility: ease with which a production system can expand as needed
7. Operation flexibility: ability to re-order manufacturing operational steps for a given part or product

8. Production flexibility: the selection of different products or part types a manufacturing process can produce.

Burstein (1988) develops a decision-making tool via a MILP to facilitate developing technology acquisition policies for an already existing manufacturing company with some inflexible production systems. They consider near-future technological advancement on production technology, though they do not consider demand to be stochastic. Fine & Freund (1990) formulate a two-stage stochastic MILP for product-flexible manufacturing capacity in which technology decisions are made in stage one, under demand uncertainty, and production decisions are made in stage two, once demand is known, according to the capacity constraints provided by the stage one decisions. Considering only two products in testing the model, they determine that the optimal solution, determining if and when to invest in product-flexible manufacturing capacity, varies depending on the correlative relationship of the two product's demand. Van Miegham (1998) similarly takes a two-stage stochastic approach, showing how the optimal solution depends on costs - capital costs of investment decision - and prices - margin on product sold. This work also suggests that the demand correlation explored in Fine & Freund (1990) is changed by costs and prices. Bish & Wang (2004) expand further, using a similar, two-stage stochastic, model and method to Van Miegham (1998) to consider a company with pricing power – the ability to change sale prices of it's products according to market information – in a monopolistic setting, and how pricing power variables affect the optimal investment decisions the effect of demand correlation.

An approach considering a multiperiod, multiproduct, and multisite problem, applied to the automotive industry is taken by Eppen et al. (1989). They propose a model which evaluates different demand scenarios (effectively extending over a 5-year period) on decisions to close, continue standard operations, or increase production capacity and flexibility for a set of sites. For each period in the demand scenario a two-stage stochastic model is solved which, in sequence, determines the capacity plan for each site and then develops a production plan according to what demand is realized for that period. For any given product, 3 demand scenarios representing pessimistic, standard, and optimistic forecasts, are generated per period. Period-to-period demand scenarios are independent of one another. They also consider the dynamics of unsatisfied demand where a portion of that from one product would transfer to another with the remainder transferring outside of the offerings from the company in question. Though the method generates solutions optimized to maximize profits for a given scenario, they suggest evaluating the output of the model against different criteria (e.g., risk) and that the preferred solution may not be one that performs best, but that performs well for all demand scenarios (i.e., robust). Chien & Zhang (2011) propose a robust optimization model for expansion decisions in the semiconductor manufacturing industry. Both semiconductors and their manufacturing technology advance very quickly and the latter is extremely capital intensive. As such capacity expansion and transformation decisions need to be made constantly by semiconductor manufacturers. This model approaches robust optimization by minimizing the potential maximum regret quantified as capacity oversupply or shortages. Jakubovskis (2017) present a two-stage robust optimization model solving for both facility location and technology choice between product-dedicated and flexible production capacity. They extend and evaluate the model over uncorrelated, negatively correlated, and positively correlated demand. The analysis of the model determines that the optimal proportion of flexible production capacity is primarily related to the cost difference between flexible and product-dedicated capacity, but that it is also sensitive to location-specific demand quantities and transportation costs.

All research found on flexible production capacity views production as a binary result – either a unit of production capacity is capable of producing a product or it is not. Unfortunately, no flexible production capacity research was found which explores the potential difference in capacity efficacy to produce products, as is the case in CEA, where different production technologies and capacity types (e.g., different lighting systems – spectra, intensity) will produce different varieties differently with respect to yield and quality.

2.3. CEA Facility Design

Given the newness of the industry, there has been limited research and academic publication, from a facility design or manufacturing optimization point of view, on indoor vertical farming operations. The resources by Kozai (2018, 2019, 202) are the "go-to" resource for most things related to indoor vertical farms, but lacks content related to facility design optimization and production optimization given the alternative methods and technologies available.

Baumont De Oliviera & Ferson (2019) identify the lack of robust business models for indoor vertical farms and associated failure without continued investment. They propose the development of a risk-based decision support system (DSS) to facilitate strategic investment for vertical farming operations. This system would make use of:

1. a database ranging across the various aspects of a vertical farming operation: technologies, costs, growing methods, etc.
2. a model library to evaluate the financial forecast for a given potential investment (new facility, new process, etc.) based on different models and risk profiles as defined by the user
3. a knowledgebase which, in concert with the database, helps guide the user to utilize their own knowledge in creating risk-registers, best practices, etc.
4. a user interface which enables interaction with the DSS.

Once completed, the DSS should help guide vertical farming organizations through understanding the risk profile of potential investments (new facilities, processes, equipment, etc.). Though good in principle, the type of DSS proposed is unlikely to be created in practice due to the required depth and breadth of information. This is further addressed in Baumont De Oliviera et al. (2022) where a lack of detailed data, poor industry standardization, and industry uncertainty is called out as a challenge to risk-enabled business planning. They provide a meta-analysis of academic and commercial analysis of VFs, highlighting the fact that most are based on hypothetical case studies, lacking detail. Further, they develop a financial risk model structure and methodology for VFs, allowing for robust assessment of potential VF business plans without complete data, and apply to two case-studies, a real VF based in the UK, and a hypothetical VF based on Japan.

Cetegen & Stuber (2021) presents a decision-making tool for CEA facility design and production scheduling development considering industry and market uncertainty. They suggest a two-pronged method considering both the trader’s perspective, dealing with market (or demand) uncertainty in developing robust crop portfolios, and the grower's perspective, developing robust optimal CEA system/facility designs and robust crop schedules considering capital costs, operational costs, and market uncertainty. These models carry out robust optimization for both considering different levels of risk tolerance and were evaluated to show the potential cost of considering risk, or the price of robustness, by comparing the value of robust optimal solutions for a case study of a crop portfolio against the same portfolio as optimized without uncertainty being considered, with deterministic inputs. Though highly technical, these models and their output are generic and applying them to a practical situation with a real CEA operation would be challenging as they rely on highly specific industry data which is not readily available.

Currently there are large gaps in the academic literature associated with the VF and CEA industries. Almost entirely, research in these areas is focused on horticultural developments. There exists a sizeable opportunity for research in the areas of business, finance, and operations research looking at these industries. This research specifically addresses three identified gaps in the current literature:

1. With different combinations of growing systems, a VF/CEA production facility can be constructed to be optimized to grow specific varieties of products. Using this principal, this research addresses how to optimally plan a complete production system for all varieties to be produced to meet projected demand.
2. For the specific production systems/technologies in this research, specifically horticultural lighting and irrigation nutrient recipes, distinct options within the range of available systems will produce different products to different effect (differing yield, differing quality). The exact effect for different production systems/technologies on individual varieties is unknown. This research suggests a technique for modelling these varying output effects. This appears to be a unique consideration in the literature associated with flexible production technology, where different production systems either can or cannot produce a product.
3. The two main areas of uncertainty/risk associated with constructing a new VF/CEA production facility are demand and the unknown production system output (yield)

effect. This research provides a method for evaluating the EVPI associated with these two areas of uncertainty.

3. METHODS/MODELS

When considering building a new VF production facility, firms like GoodLeaf must consider the appropriate size of facility to build according to uncertain demand, and what combinations of lighting and irrigation nutrient recipe systems to include in the design according to current understand of their associated effect on output. Using two sequential MILP formulations, this method generates a set of feasible facility design options for evaluation.

For a set, N, of potential demand scenarios, the method solves, via "model 1", for each demand scenario, the optimal facility design with respect to total profit over the demand horizon, by making both technology/production capacity investment decisions and production planning (capacity assignment) decisions. The method then, for each demand scenario's optimal production capacity solution, solves, via "model 2", production planning (capacity assignment) against a realization of every other demand scenario. The result is N technology/capacity solutions, or facility designs, each with N production planning solutions. Figure 2 shows a schematic of the solution process for the method.

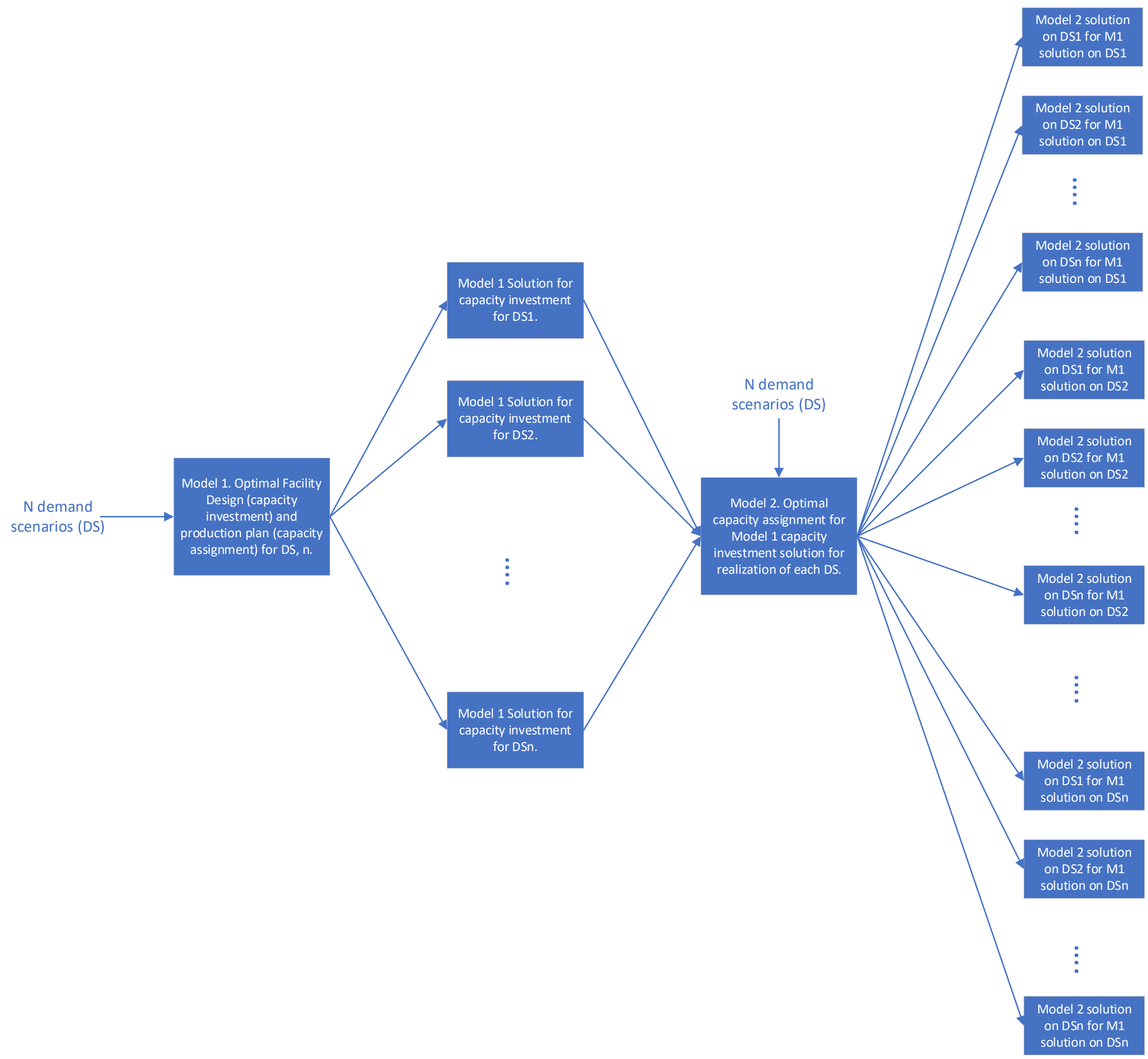

Figure 2. Method schematic

In the context of a vertical farming operation a "demand scenario" references the projected periodic (weekly, monthly, annual, etc.) total demand for each variety of product to be grown over a specified time horizon. For example, the total annual demand for a baby kale product could be 100,000 kgs. Realistic demand scenarios can be generated from market research, analysis, and forecasting. Further, "edge case" scenarios can be generated to create a robust set of potential production capacity designs.

Production capacity refers to a unit of grow chamber space outfitted with a specific set of production technology. Units of grow chamber space must be pre-defined for the model.

For example, a single layer of racking in a grow chamber could be defined as a single unit of production capacity. A unit of production capacity could then be outfitted with several types of lighting technology (variety-specific, universal, flexible-controllable) and irrigation systems (number of connections to different nutrient recipes). Depending on the type of technology a unit of production capacity has, it will be either more or less effective, in terms of saleable yield, at producing a given variety of product.

To estimate the production output for a unit of production capacity with a specific set of technologies, sets of scale factors for each variety and technology are constructed and applied. First, a perfect unit output (PUO) is set for each variety to be produced by the facility. That is, under perfect conditions, i.e., with the perfect production technology for that variety, how much output per period would be achieved by a unit of production capacity, dimensionally, in mass/unit time. There are I different PUOs, one for each variety. Then, for each technology (lighting or irrigation), a scale factor is set for each variety being produced with each type of each technology as the percentage of PUO to be achieved for a unit of capacity. For lighting factors (LF) there will be $I\,x\,L$ technology scale factors. For irrigation recipe factors (RF) there will be $I\ x\ R$ technology scale factors. Finally, technology interaction factors (IF) are considered as a combination of lighting and irrigation recipes may result in a different yield effect than just the product of the two factors. There will be $I\,x\,L\,x\,R$ technology interaction factors. Therefore, a given periodic output of a unit of production capacity, is calculated as $o_{ilr} = PUO * LF * RF * IF.$ As explored in Section 2.1.1, there is evidence to suggest that different lighting system setups with different spectra and intensity, combined with different nutrient system setups having different irrigation styles, nutrient makeups, etc., can have a significant effect on output quantity and quality. The exact effect that these different input parameters may have on different varieties is unknown and bears further research. Thus, in section 4.3, we explore reformatting the technology selection method to take a single demand scenario as input and a range of possible technology scale factors. This allows us to infer an expected value of perfect information (EVPI) associated with a company like GoodLeaf better understanding the value of researching the effect these different production technologies may have on their products.

3.1. MODEL FORMULATION

The notation used in the models developed for this thesis are as follows:

Table 1. Model notation

Notation	Description
Index sets and indices	
I	Set of varieties of LGVs to produce (e.g., baby arugula, micro radish, etc.)
J	Set of time periods for demand scenarios (e.g., year 1, year 2, etc.)
L	Set of lighting system types
R	Set of nutrient recipe connection types
Q	Set of nutrient recipe types
$m1$	Denotes variable value from solution to model 1
$m2$	Denoted variable for model 2
Design Variables	
z_{ijlr}	Production planning/capacity assignment variable. Amount of production capacity of lighting system type l and recipe connection type r dedicated to produce variety i in period j.
x_{lr}	Capacity Design/Technology investment variable. Units of production capacity of lighting system type l and recipe connection type r to build into facility.
y_{ij}^{+}	Amount of overproduction (exceeding demand) of variety i in period j
y_{ij}^{-}	Amount of underproduction (not meeting demand) of variety i in period j
w_q	Number of unique per-stack nutrient recipe connections per recipe type
t	Number of stacks of racking to build in the grow chamber
g	Number of racking bays to build in the germination chamber
s^p	Number of packaging systems to design into the facility
s^s	Number of seeding systems to design into the facility
s^h	Number of harvesting and cleaning systems to design into the facility
s^a	Amount of auxiliary space to design into the facility (offices, welfare space, etc.)
s^{fg}	Amount of finished goods inventory racking bays to design into the facility
s^{rg}	Amount of raw goods inventory racking bays to design into the facility
s^{MHE}	Number of table handling systems (lifters, conveyors, etc.) needed for facility
Parameters	
o_{ilr}	Annual output of a unit of production capacity of lighting system type l and recipe connection type r producing variety type i
p_i	Sale price per unit output of variety i
d_{ij}	Demand for variety i in period j
v_{rq}	Recipe type r included in recipe connection type q

b^{+}	Percent sale price discount for excess product (overproduction)
S	Number of units of production per stack in grow chamber
D	Periodic cash flow discount rate
c_i^{proc}	Unit cost of post-production processing (packaging and freight) for production of variety i
c_i^{prod}	Production capacity unit cost of production (power, water, inputs, etc.) for variety i
c_i^{-}	Unit cost of underproduction for variety i
c_r^{r}	Per production capacity unit cost of recipe connection type r
c_l^{l}	Per production capacity unit cost of lighting system type l
c^{w}	Cost per stack recipe connections
c^{gr}	Cost of racking per stack of grow chamber racking
c^{ge}	Cost of racking per bay of germination racking
c^{p}	Cost per packaging system
c^{s}	Cost per seeding system
c^{h}	Cost per harvest and cleaning systems
c^{b}	Cost per bay of storage (raw goods and finished goods) racking
c^{a}	Cost per unit area (construction and fit-up) of built out space
c^{MHE}	Cost per table handling (lifters, conveyors, etc.) system
a^{gr}	Area required per stack of grow chamber racking
a^{ge}	Area required per bay of germination racking
a^{p}	Area required per packaging system
a^{s}	Area required per seeding system
a^{h}	Area required per harvest and cleaning systems
a^{b}	Area required per bay of storage (raw goods and finished goods) racking
a^{a}	Unit area of auxiliary built-out space
f_i^{ge}	Germination system sizing factor
f^{p}	Packaging system sizing factor
f^{s}	Seeding system sizing factor
f^{h}	Harvest and cleaning system sizing factor
f^{fg}	Finished goods inventory space sizing factor
f^{rg}	Raw goods inventory space sizing factor
f^{MHE}	Table handling system sizing factor
f^{a}	Auxiliary space (hallways, bathrooms, etc.) sizing factor

3.1.1. Model 1

The first of two MILP models used by the method, Model 1 (M1) takes the following form:

$$\max_{j \in J} \quad \sum_j \Bigg[\Bigg[\sum_i \sum_l \sum_r z_{ijlr} \left(o_{ilr} \left(p_i - c_i^{proc} \right) - c_i^{prod} \right) - \sum_i y_{ij}^{+} p_i b^{+} - \sum_i c_i^{-} y_{ij}^{-} \Bigg] \left(\frac{1}{(1+D)^j} \right) - \sum_r \sum_l x_{lr} \left(c_r^r + c_l^l \right) - \sum_q w_q c^w - t(c^{gr} + a^{gr} c^a) - g(c^{ge} + a^{ge} c^a) - s^p (c^p + a^p c^a) - s^s (c^s + a^s c^a) - s^h (c^h + a^h c^a) - s^{fg} (c^b + a^b c^a) - s^{rg} (c^b + a^b c^a) - s^{MHE} c^{MHE} - s^a a^a c^a \Bigg] \tag{1}$$

Subject to:

$$\sum_i z_{ijlr} \leq x_{lr} \qquad \forall r, \forall l, \forall j \tag{2}$$

$$\sum_l \sum_r z_{ijlr} o_{lr} - y_{ij}^{+} + y_{ij}^{-} = d_{ij} \qquad \forall i, \forall j \tag{3}$$

$$w_q \geq \sum_l \sum_r v_{rq} \frac{x_{lr}}{S} \qquad \forall q \tag{4}$$

$$t = \sum_l \sum_r \frac{x_{lr}}{S} \tag{5}$$

$$g \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} f_i^{ge} \qquad \forall j$$

(6)

$$s^p \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} o_{ilr} f^p \qquad \forall j$$

(7)

$$s^s \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} o_{ilr} f^s \qquad \forall j$$

(8)

$$s^h \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} o_{ilr} f^h \qquad \forall j$$

(9)

$$s^a \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} o_{ilr} f^a \qquad \forall j$$

(10)

$$s^{fg} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} o_{ilr} f_i^{fg} \qquad \forall j$$

(11)

$$s^{rg} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} o_{ilr} f_i^{rg} \qquad \forall j$$

(12)

$$s^{MHE} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} o_{ilr} f^{MHE} \qquad \forall j$$

(13)

$$z_{ijlr}, x_{lr}, t, w_q, g, s^p, s^s, s^h, s^{fg}, s^{rg}, s^{MHE} \sim int$$

(14)

3.1.1.1. Objective Function

The objective function, Equation (1), is set to maximize total profit over the entire forecast time for a demand scenario. The first term accounts for all sales profit of produced and sold product, less the processing costs (packaging and freight). The second term subtracts from total profit by the amount of overproduction for each variety, for each production period, by applying an excess product discount. The third term accounts for the operating costs of each unit of production capacity. The fourth term accounts for the shorting, or underproduction, cost of each variety. These first four terms are multiplied by a cashflow discount rate to adjust future period profits to current-time value. The fifth term accounts for the construction costs of all installed units of production capacity. The sixth term accounts for all per-stack irrigation connection installation costs. The seventh term accounts for all grow chamber racking and space costs. The eighth term accounts for all germination chamber racking and space costs. The ninth term accounts for all packaging systems and space costs. The tenth term accounts for all seeding systems and space costs. The eleventh term accounts for all harvest and cleaning systems and space costs. The twelve and thirteenth terms account for inventory storage racking and space costs. The fourteenth term accounts for all table handling automation system costs. The final term accounts for all auxiliary space, such as office space and welfare area, costs.

3.1.1.2. Constraints

Equation (2) constrains production allocation such that the production of a given variety in each period can only occur on units of production capacity that exist.

Equation (3) constrains production for each variety for each period to meet demand. The inclusions of overproduction and underproduction variables allow slack in the model. These are priced into the objective function accordingly. Overproduction is sold at a discount whereas underproduction is penalized via reputational dollar value.

Equation (4) constrains the number of per-stack irrigation connections.

Equation (5) constrains the total units of production capacity to fit into complete stacks of grow chamber racking.

Equation (6) constrains the amount of germination racking based on grow chamber production assignment and the germination sizing factor (based on ratio of variety germination time and grow time).

Equation (7) constrains the number of packaging systems based on the total output and the packaging system sizing factor.

Equation (8) constrains the number of seeding systems based on the total output and the seeding system sizing factor.

Equation (9) constrains the number of harvest and cleaning systems based on the total output and the harvest and cleaning system sizing factor.

Equation (10) constrains the amount of auxiliary space based on the total output and the auxiliary space sizing factor.

Equation (11) constrains the amount of finished goods inventory racking based on the total output and the finished goods inventory sizing factor.

Equation (12) constrains the amount of raw goods inventory racking based on the total output and the raw goods inventory sizing factor.

Equation (13) constrains the number of table handling automation systems based on the total output and the table handling automation system factor.

Equation (14) are integer constraints for the variables in question (all but overproduction, underproduction, and auxiliary space).

3.1.2. Model 2

The second of two MILP models used by the method, Model 2 (M2) takes the following form:

(15)

$$\max_{j\in J} \quad \sum_j \Bigg[\Bigg[\sum_i \sum_l \sum_r {z_{ijlr}}^{m2}\left(o_{ilr}\left(p_i - c_i^{proc}\right) - c_i^{prod}\right) - \sum_i y_{ij}^{+m2} p_i b^+ - \sum_i c_i^- y_{ij}^{-m2}\Bigg]\left(\frac{1}{(1+D)^j}\right) - \sum_r \sum_l {x_{lr}}^{m2}\left(c_r^r + c_l^l\right)$$
$$- \sum_q {w_q}^{m2} c^w - t^{m2}(c^{gr} + a^{gr} c^a) - g^{m2}(c^{ge} + a^{ge} c^a)$$
$$- s^{pm2}(c^p + a^p c^a) - s^{sm2}(c^s + a^s c^a) - s^{hm2}(c^h + a^h c^a)$$
$$- s^{fgm2}(c^b + a^b c^a) - s^{rgm2}(c^b + a^b c^a) - s^{MHEm2} c^{MHE}$$
$$- s^{am2} a^a c^a \Bigg]$$

Subject to:

$$ {x_{lr}}^{m2} = {x_{lr}}^{m1} \qquad \forall r, \forall l$$

(16)

$$\sum_i {z_{ijlr}}^{m2} \le {x_{lr}}^{m2} \qquad \forall r, \forall l, \forall j$$

(17)

$$\sum_l \sum_r {z_{ijlr}}^{m2} o_{lr} - y_{ij}^{+m2} + y_{ij}^{-m2} = d_{ij} \qquad \forall i, \forall j$$

(18)

$$w_q{}^{m2} = w_q{}^{m1} \qquad \forall q$$

(19)

$$t^{m2} = t^{m1}$$

(20)

$$g^{m2} = g^{m1}$$

(21)

$$s^{pm2} = s^{pm1}$$

(22)

$$s^{sm2} = s^{sm1}$$

(23)

$$s^{hm2} = s^{hm1}$$

(24)

$$s^{fgm2} = s^{fgm1}$$

(25)

$$s^{rgm2} = s^{rgm1}$$

(26)

$$s^{MHEm2} = s^{MHEm1}$$

(27)

$$s^{am2} = s^{am1}$$

(28)

$$g^{m2} \geq \sum_i \sum_l \sum_r z_{ijlr}{}^{m2} f_i^{ge} \qquad \forall j$$

(29)

$$s^{pm2} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr}{}^{m2} o_{ilr}\, f^{p} \qquad \forall j$$

(30)

$$s^{sm2} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr}{}^{m2} o_{ilr}\, f^{s} \qquad \forall j$$

(31)

$$s^{hm2} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr}{}^{m2} o_{ilr}\, f^{h} \qquad \forall j$$

(32)

$$s^{am2} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr}{}^{m2} o_{ilr}\, f^{a} \qquad \forall j$$

(33)

$$s^{fgm2} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr}{}^{m2} o_{ilr} f_{i}^{fg} \qquad \forall j$$

(34)

$$s^{rgm2} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr}{}^{m2} o_{ilr} f_{i}^{rg} \qquad \forall j$$

(35)

$$s^{MHEm2} \geq \sum_{i} \sum_{l} \sum_{r} z_{ijlr} o_{ilr}\, f^{MHE} \qquad \forall j$$

(36)

$$z_{ijlr}{}^{m2}, x_{lr}{}^{m2}, t^{m2}, w_{q}{}^{m2}, g^{m2}, s^{pm2}, s^{sm2}, s^{hm2}, s^{fgm2}, s^{rgm2} \sim int$$

(37)

3.1.2.1. Objective Function

The objective function, Equation (15), for M2 is the exact same as that for M1 with all variables in the objective function as the M2 version of the variables

3.1.2.2. Constraints

Equation (16) sets all M2 production capacities to be built into the facility, equal to that of the solution from M1. This enforces that the only available production capacity for allocating periodic production per M2 is the solution from M1.

Equation (17) ensures that, for M2, production is only allocated to production capacity that exists.

Equation (18) is the demand constraint for M2.

Equations (19) through (28) ensure that all non-production capacity design variables (e.g., per-stack recipe connections, packaging systems, etc.) are constrained to be the same as the solution from M1

Equations (29) through (36) further constrain the production allocation by enforcing throughput rules according to the capacity of design variables (e.g., germination space, packaging systems, etc.)

4. ANALYSIS

Based on experience in the industry and with GoodLeaf farms, a representative case study has been developed to test this method. All values and information used as input have been altered (compared to real-world) to maintain privacy for GoodLeaf's industrial knowhow.

Company A, a vertical farming company specializing in producing LGVs, is planning to construct a new large-scale production facility in a location representing a brand-new market for their products. Company A is at the size and scale where the design of their production systems is somewhat boilerplate and makes use of vendor partnerships and system standardization. They utilize standard 20" x 10" grow trays, mobile ebb and flood tables and irrigation methods, FIFO-style passive conveyance in their grow chambers, LED single-source lighting, single-chamber climate control, automated seeding, harvesting, packaging, and cleaning systems.

In their other facilities, Company A has used static lighting with a single spectrum for the entire facility. This has worked well, but Company A's leadership suspect that, for this new facility, specialized spectra for different varieties may provide some value by way of increased yield per crop. The horticulturalists at the company agree, but the exact effect is unknown.

Similarly, Company A has used simple ebb and flood irrigation system design in their facilities to date, with only a single nutrient feed available for all production capacity. Again, this has worked well, but there are thoughts that specialized nutrient recipes for different varieties can improve yields. Again, the exact effect is unknown.

Company A plans to produce 5 varieties of LGVs from the new production facility. They have high-level demand forecasts for these products, but due to the newness of the market to the product category, exact forecasts are difficult to predict. A range of equally likely potential demand forecasts for the first ten years of operation for the facility have been generated according to Company A's commercial outlook.

The previously discussed method for selecting production capacity technology and overall facility design decisions will be used to help Company A decide how best to design this new facility.

4.1. Case study Assumptions

The following sections outline modelling assumptions associated with:

- production capacity technology,
- facility layout, costs, prices, and general modelling parameters, and
- demand scenarios

4.1.1. Output Factors

As discussed, the exact effect of different lighting and irrigation recipes on production output for specific varieties is unknown. The first application of this method will evaluate two different scenarios with respect to the output factors. The first, "narrow" yield factor scenario, will assume a narrow range of differences for both LFs and RFs across the different varieties. The second, "wide" yield factor scenario, will assume a wide range of difference for both LFs and RFs across the different varieties. Both scenarios will assume all IFs = 0 between the two technologies. This evaluation will also determine the EVPI with respect to demand uncertainty within the demand scenarios used.

Further, a second application of the method will, for a single demand scenario, evaluate a range of potential output factor effects to similarly provide system design options and determine, for that demand scenario, the EVPI with respect to these horticultural factors.

4.1.1.1. Narrow Yield Factor Scenario

The LFs applied to the "narrow" scenario can be seen in Table 2.

Table 2. Lighting yield factor assumptions for "narrow" scenario.

	Lighting System						
Variety	Variety 1	Variety 2	Variety 3	Variety 4	Variety 5	Universal	Flexible
1	1	0.85	0.85	0.8	0.8	0.8	1
2	0.8	1	0.8	0.9	0.9	0.9	1
3	0.86	0.9	1	0.85	0.8	0.9	1
4	0.9	0.8	0.9	1	0.8	0.9	1
5	0.8	0.9	0.9	0.9	1	0.85	1

e.g., If variety 1 is produced on a unit of production capacity using a variety 2 lighting system, it will result in a 15% reduction in commercially viable yield.

The RFs applied to the "narrow" scenario can be seen in Table 3.

Table 3. Irrigation yield factor assumptions for "narrow" scenario

	Nutrient Recipe			
Variety	Recipe 1	Recipe 2	Recipe 3	Recipe 4
1	1	0.8	0.9	0.8
2	1	0.8	0.85	0.85
3	1	0.85	0.8	0.9
4	0.8	1	0.9	0.9
5	0.85	0.9	1	0.85

e.g., If variety 1 is produced on a unit of production capacity with connections to both recipe 2 and recipe 3, the best performing recipe will be used, recipe 3, resulting in a 10% reduction in commercially viable yield.

4.1.1.2. *Wide Yield Factor Scenario*

The LFs applied to the "wide" scenario can be seen in Table 4.

Table 4. Lighting yield factor assumptions for "wide" scenario.

	Lighting System						
Variety	Variety 1	Variety 2	Variety 3	Variety 4	Variety 5	Universal	Flexible
1	1	0.5	0.5	0.5	0.5	0.7	1
2	0.2	1	0.2	0.2	0.2	0.7	1
3	0.2	0.2	1	0.2	0.2	0.7	1
4	0.5	0.5	0.5	1	0.5	0.7	1
5	0.2	0.2	0.2	0.2	1	0.7	1

e.g., If variety 2 were produced on a unit of production capacity using a universal lighting system, it will result in a 30% reduction in commercially viable yield

The RFs applied to the "wide" scenario can be seen in Table 5.

Table 5. Irrigation yield factor assumptions for "wide" scenario.

	Nutrient Recipe			
Variety	Recipe 1	Recipe 2	Recipe 3	Recipe 4
1	1	0.5	0.5	0.75
2	1	0.2	0.2	0.5
3	1	0.2	0.2	0.5
4	0.5	1	0.2	0.5
5	0.5	0.2	1	0.5

e.g., If variety 2 were produced on a unit of production capacity with connections to both recipe 3 and recipe 4, it will result in a 50% reduction in commercially viable yield.

4.1.1.3. PERFECT UNIT OUTPUT

For each of the 5 varieties, a single unit of production capacity (in this case, a single layer of grow chamber racking) will, under perfect lighting and irrigation inputs, have the annual outputs as seen in Table 6.

Table 6. Annual PUO for each variety (kg).

	Variety				
	1	2	3	4	5
Annual PUO (kg)	12,500	10,000	10,000	5,000	4,000

As can bee seen from Table 6, the varieties are grouped into two distinct categories, "high yield" and "low yield". Varieties 1, 2, and 3 are considered "high yield" and are meant to reflect real world examples of varieties with short grow cycle times (e.g., micro greens). Varieties 4 and 5 are considered "low yield" and are meant to reflect real world examples of varieties with long grow cycle times (e.g., baby greens).

The PUO and yield factors are then used to calculate the values of o_{ilr}. For example, in these first applications of the method, where the interaction factor for lighting and irrigation systems are assumed to be 1, under the "narrow" yield factor scenario, if variety 1 ($PUO = 12{,}500\ kg$) were produced on a unit of production capacity with lighting system "variety 1" ($LF = 1$) and an irrigation system with connections to recipes 3 and 4 ($RF = 0.9$), the value of $o_{ilr} = 12{,}500kg * 1 * 0.9 = 11{,}250kg$.

4.1.2. Layout, Economics, and Throughputs

- A layer of grow chamber racking is considered a "unit" of production capacity which can be outfitted with different production technologies (lighting systems, irrigation systems).
- Each layer of grow chamber racking contain 12 table locations.
- Each stack of grow chamber racking contains 10 layers and occupies 91.1 m^2.
- A bay of germination racking contains 56 table locations – 2 bays, 14 layers tall, double-deep table locations – and occupies 47.5 m^2.
- Packaging systems, seeding systems, harvest and cleaning systems, and storage racking bays occupy 185.8 m^2, 325.1 m^2, 418.1 m^2, and 15.0 m^2 respectively
- A unit of auxiliary space is 0.1 m^2
- There are 600 production minutes available in a day.
- Sales prices, processing costs, and annual operating costs per variety are:

Table 7 . Sale price, processing, and operating costs per variety

Variety	*Sale Price ($/kg)*	*Processing Costs ($/kg)*	*Operating Costs ($/layer/year)*
1	44.51	5.11	105,543.36
2	44.51	5.11	68,786.64
3	44.51	5.11	48,035.52
4	22.00	4.22	40,818.16
5	22.00	4.22	40,218.02

- Shorting costs are 50% sales price (e.g., for each kg of variety shorted to a customer, Company A incurs a penalty of $22.25)
- Excess product will be sold at a 75% discount.
- The per-unit (layer) cost of a recipe connection is $32,000. (e.g., if a layer were to be connected to recipe 1 and 2, it would cost $64,000).
- A layer of dedicated or universal lighting costs $33,500 while a layer of flexible lighting costs $48,000
- A stack of grow chamber racking, including tables and trays, costs $172,000.00
- A bay of germination racking costs $66,000.00
- A packaging system costs $2,475,000.00 and can process 3.5 kg/minute of product
- A seeding system costs $655,000.00 and can process 3.5 kg/minute of product
- A harvest and cleaning system costs $1,000,000.00 and can process 3.5 kg/min of product
- A bay of storage racking costs $2,000.00. Company A requires 5 days worth of finished goods inventory storage and 7 days worth of raw goods inventory storage
- The infrastructure required to connect an irrigation recipe to a single stack of grow chamber racking costs $375,000.00 per connection.
- An automated material handling system for moving product through the operation costs $2,500,000.00 and can run at a rate equivalent to 3.5 kg/min of finished product.
- Building construction and fit-up costs $3330.00/$m^2$
- The cashflow discount rate for Company A will be 15%

4.1.3. DEMAND SCENARIOS

To explore the breadth of potential facility designs and capabilities for the first application of this method, ten different demand scenarios (DS) have been generated. Each DS forecasts, for each variety, the total demand per year (kgs), for a ten-year forecast horizon. Each DS can be seen in Table 8 through Table 17.

Table 8. Demand Scenario 1 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	25,000	35,000	45,000	55,000	65,000	75,000	85,000	95,000	105,000	115,000
Variety 2	75,000	80,000	85,000	90,000	95,000	100,000	105,000	110,000	115,000	120,000
Variety 3	75,000	80,000	85,000	90,000	95,000	100,000	105,000	110,000	115,000	120,000
Variety 4	115,000	125,000	135,000	145,000	155,000	165,000	175,000	185,000	195,000	205,000
Variety 5	115,000	125,000	135,000	145,000	155,000	165,000	175,000	185,000	195,000	205,000

DS1 represents a consistent annual increase in demand across all varieties.

Table 9. Demand Scenario 2 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	72,500	70,000	67,500	65,000	62,500	60,000	57,500	55,000	52,500
Variety 2	75,000	70,000	65,000	60,000	55,000	50,000	45,000	40,000	35,000	30,000
Variety 3	75,000	72,000	69,000	66,000	63,000	60,000	57,000	54,000	51,000	48,000
Variety 4	115,000	105,000	95,000	85,000	75,000	65,000	55,000	45,000	35,000	25,000
Variety 5	115,000	105,000	95,000	85,000	75,000	65,000	55,000	45,000	35,000	25,000

DS2 represents a consistent annual decrease in demand across all varieties.

Table 10. Demand Scenario 3 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	77,000	78,000	80,000	82,000	84,000	86,000	89,000	90,000	92,000
Variety 2	75,000	78,000	81,000	83,000	85,000	88,000	90,000	93,000	94,000	96,000
Variety 3	75,000	77,000	79,000	82,000	85,000	87,000	89,000	92,000	95,000	99,000
Variety 4	115,000	122,000	133,000	137,000	141,000	147,000	155,000	159,000	158,000	167,000
Variety 5	115,000	119,000	128,000	132,000	136,000	143,000	142,000	144,000	148,000	157,000

DS3 represents a random annual increase in demand across all varieties.

Table 11. Demand Scenario 4 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	72,000	68,000	66,000	62,000	60,000	57,000	55,000	52,000	51,000
Variety 2	75,000	72,000	69,000	66,000	63,000	60,000	58,000	55,000	52,000	50,000
Variety 3	75,000	72,000	70,000	67,000	65,000	62,000	60,000	56,000	53,000	50,000
Variety 4	115,000	108,000	100,000	95,000	91,000	85,000	78,000	68,000	68,000	67,000
Variety 5	115,000	108,000	99,000	93,000	86,000	77,000	74,000	67,000	61,000	56,000

DS4 represents a random annual decrease in demand across all varieties.

Table 12. Demand Scenario 5 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	76,000	74,000	77,000	71,000	64,000	81,000	73,000	73,000	88,000
Variety 2	75,000	77,000	73,000	75,000	71,000	78,000	81,000	65,000	73,000	79,000
Variety 3	75,000	71,000	82,000	68,000	66,000	79,000	77,000	66,000	76,000	76,000
Variety 4	115,000	119,000	123,000	129,000	128,000	135,000	139,000	145,000	149,000	155,000
Variety 5	115,000	122,000	124,000	130,000	132,000	140,000	147,000	151,000	159,000	159,000

DS5 represents a random annual increase for the "low yield" varieties (4 and 5) and randomly consistent annual demand for the "high yield" varieties (1, 2, and 3).

Table 13. Demand Scenario 6 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	53,000	61,000	129,000	65,000	169,000	55,000	114,000	90,000	116,000
Variety 2	75,000	32,000	115,000	76,000	65,000	39,000	122,000	181,000	84,000	20,000
Variety 3	75,000	66,000	82,000	104,000	121,000	80,000	121,000	101,000	87,000	167,000
Variety 4	115,000	99,000	94,000	65,000	53,000	61,000	122,000	136,000	153,000	160,000
Variety 5	115,000	129,000	73,000	119,000	160,000	112,000	179,000	37,000	47,000	97,000

DS6 represents randomly consistent annual demand with a high level of variance across all varieties.

Table 14. Demand Scenario 7 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	78,000	68,000	75,000	84,000	73,000	81,000	37,000	60,000	82,000
Variety 2	75,000	55,000	67,000	62,000	104,000	74,000	86,000	65,000	100,000	41,000
Variety 3	75,000	71,000	62,000	87,000	72,000	69,000	95,000	98,000	73,000	64,000
Variety 4	115,000	106,000	103,000	125,000	103,000	117,000	113,000	138,000	108,000	111,000
Variety 5	115,000	74,000	111,000	123,000	123,000	131,000	134,000	115,000	116,000	84,000

DS7 represents randomly consistent annual demand with a moderate level of variance across all varieties.

Table 15. Demand Scenario 8 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	78,000	75,000	71,000	77,000	74,000	73,000	70,000	73,000	74,000
Variety 2	75,000	75,000	77,000	71,000	75,000	76,000	70,000	74,000	74,000	75,000
Variety 3	75,000	77,000	76,000	78,000	76,000	78,000	74,000	73,000	77,000	75,000
Variety 4	115,000	116,000	121,000	115,000	114,000	111,000	118,000	114,000	116,000	120,000
Variety 5	115,000	113,000	114,000	118,000	118,000	116,000	114,000	118,000	114,000	116,000

DS8 represents randomly consistent annual demand with a low level of variance across all varieties.

Table 16. Demand Scenario 9 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	74,000	73,000	70,000	67,000	66,000	63,000	61,000	58,000	56,000
Variety 2	75,000	71,000	68,000	64,000	62,000	59,000	57,000	54,000	50,000	48,000
Variety 3	75,000	71,000	67,000	64,000	61,000	58,000	57,000	54,000	49,000	46,000
Variety 4	115,000	121,000	124,000	132,000	138,000	143,000	151,000	158,000	163,000	164,000
Variety 5	115,000	124,000	136,000	139,000	145,000	149,000	155,000	159,000	160,000	165,000

DS9 represents a random annual increase in demand for “low yield” varieties (4 and 5) and a random annual decrease in demand for “high yield” varieties (1, 2, and 3).

Table 17. Demand Scenario 10 (kg/year).

Variety	Demand Period									
	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Variety 1	75,000	78,000	79,000	82,000	83,000	86,000	89,000	92,000	94,000	95,000
Variety 2	75,000	77,000	80,000	84,000	85,000	88,000	92,000	95,000	97,000	101,000
Variety 3	75,000	78,000	80,000	84,000	86,000	89,000	90,000	93,000	96,000	100,000
Variety 4	115,000	109,000	112,000	107,000	102,000	95,000	88,000	87,000	84,000	77,000
Variety 5	115,000	110,000	101,000	100,000	95,000	91,000	84,000	78,000	76,000	70,000

DS9 represents a random annual decrease in demand for “low yield” varieties (4 and 5) and a random annual increase in demand for “high yield” varieties (1, 2, and 3).

4.2. Results 1 – Different Demand Scenarios

The first two applications of the proposed method will profit-optimize, for each DS, a facility model for a specific set of yield factors, then optimize production allocation for that facility model against each DS. For *N*-DSs, the results will be an *N* x *N* matrix showing how each demand-scenario-optimized facility model performs against each DS. These results can then be analyzed against any arbitrary set of criteria. To demonstrate this, the following seven criteria have been selected for analysis.

Criteria 1. Average Profit. For any of the *N* models, the average of the expected total profits, for that facility model, across all DSs.

Criteria 2. Minimum Profit. For any of the *N* models, the minimum of the expected total profits, for that facility model, across all DSs.

Criteria 3. Maximum Profit. For any of the *N* models, the maximum of the expected total profits, for that facility model, across all DSs.

Criteria 4. Regret. For any of the *N* models, the sum, across all DSs, of the differences between how that facility model performs on a DS and how the demand-scenario-optimized facility model performs on that DS.

Criteria 5. Average Time to Net-0 (TTN0). For any of the *N* facility models, the average of the expected times for the modelled facility to fully pay back on its initial capital investment across all DSs.

Criteria 6. Maximum TTN0. For any of the N facility models, the maximum of the expected times for the modelled facility to fully pay back on its initial capital investment across all DSs.

Criteria 7. Minimum TTN0. For any of the N facility models, the minimum of the expected times for the modelled facility to fully pay back on its initial capital investment across all DSs.

Evaluating the model performance with these criteria can be done according to the preferences of the organization in question. As an example, we will apply a sum-total rank score and solution where all dominated solutions are removed from consideration.

4.2.1. Narrow Yield Factor Results

The first application of the proposed method applies the "narrow" LFs and RFs and assumes all IFs = 0. The expected profit results of applying the method can be seen in Table 18.

Table 18. Summary results for narrow yield factors ($mm).

	Model									
Demand Scenario	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
1	27.104	16.774	26.665	20.722	25.115	26.439	24.329	24.228	24.825	24.159
2	13.007	17.344	13.342	17.279	14.671	15.236	16.513	16.430	14.901	16.412
3	27.437	20.334	27.773	23.658	27.243	27.627	26.575	26.516	26.541	26.210
4	15.369	18.708	15.683	19.142	17.105	17.517	18.863	18.822	17.330	18.798
5	23.390	19.170	23.922	21.215	24.702	24.000	23.578	23.625	24.348	23.241
6	27.484	21.161	27.433	25.254	27.666	28.806	28.286	28.159	27.636	28.287
7	21.597	20.220	22.062	22.221	23.188	23.413	23.720	23.631	23.144	23.501
8	22.688	21.577	23.265	23.007	24.572	24.620	25.067	25.076	24.850	24.950
9	18.826	14.782	19.458	16.716	20.233	19.285	19.000	19.027	20.389	18.629
10	25.730	24.574	26.014	26.665	27.470	27.775	28.614	28.549	27.554	28.831

In this table, a "model" is the specific facility with a specific set of production technologies that the method selects to optimize for a given DS (e.g., model 7 is the facility model optimized for DS7). The data in the table represents the expected total 10-year profit of each optimized model against each DS (e.g., if model 5 was built and DS7 was realized, the expected 10-year profit would be $23,188,000). A verification that the method is behaving appropriately is that, for each DS, the best performing model, in terms of maximum profit, must be that which is optimized for that DS. Therefor, in this table the diagonal must be the maximum expected profit in each row.

The TTN0 results of applying the method can be seen in Table 19.

Table 19. TTN0 results for narrow yield factors (years).

	Model									
Demand Scenario	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
1	4.34	3.95	4.25	3.96	4.03	4.10	3.91	3.91	4.01	3.97
2	4.79	3.62	4.68	3.72	4.28	4.26	3.87	3.87	4.21	3.89
3	4.04	3.58	3.94	3.60	3.71	3.77	3.59	3.59	3.73	3.63
4	4.65	3.63	4.55	3.71	4.15	4.16	3.80	3.80	4.10	3.82
5	4.21	3.63	4.10	3.68	3.79	3.86	3.66	3.66	3.78	3.70
6	4.20	3.69	4.13	3.68	3.89	3.87	3.67	3.67	3.87	3.69
7	4.51	3.73	4.42	3.81	4.14	4.15	3.88	3.88	4.11	3.91
8	4.23	3.53	4.12	3.61	3.82	3.86	3.62	3.61	3.77	3.63
9	4.40	3.85	4.29	3.88	3.95	4.06	3.83	3.83	3.92	3.88
10	4.12	3.43	4.03	3.51	3.75	3.77	3.52	3.52	3.72	3.53

As the method is optimizing facility design for total profit per DS, the same verification (each model performs best for its specific DS) does not apply for TTN0 (e.g., for DS1, models 7 and 8 perform better, with a faster TTN0, than model 1).

The regret results of applying the method can be seen in Table 20.

Table 20. Regret results for Narrow yield factors ($mm).

	Model									
Demand Scenario	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
1	-	-10.329	- 0.438	- 6.381	- 1.988	- 0.665	- 2.774	- 2.875	- 2.279	- 2.944
2	- 4.337	-	- 4.002	- 0.065	- 2.674	- 2.108	- 0.831	- 0.914	- 2.443	- 0.933
3	- 0.337	- 7.439	-	- 4.115	- 0.531	- 0.147	- 1.198	- 1.258	- 1.233	- 1.563
4	- 3.773	- 0.434	- 3.458	-	- 2.037	- 1.624	- 0.279	- 0.319	- 1.812	- 0.344
5	- 1.312	- 5.532	- 0.780	- 3.486	-	- 0.702	- 1.123	- 1.076	- 0.353	- 1.460
6	- 1.322	- 7.645	- 1.373	- 3.551	- 1.140	-	- 0.520	- 0.647	- 1.169	- 0.519
7	- 2.123	- 3.501	- 1.658	- 1.499	- 0.532	- 0.308	-	- 0.090	- 0.576	- 0.219
8	- 2.388	- 3.500	- 1.811	- 2.069	- 0.505	- 0.456	- 0.009	-	- 0.227	- 0.127
9	- 1.563	- 5.607	- 0.931	- 3.673	- 0.156	- 1.104	- 1.389	- 1.362	-	- 1.760
10	- 3.101	- 4.257	- 2.817	- 2.166	- 1.361	- 1.055	- 0.217	- 0.282	- 1.276	-

As an example of a regret criteria results, if the model 2 facility was constructed and DS1 occurred, company A could have realized $10,329,000 more in profit over the demand horizon had they constructed the model 1 optimized facility.

The seven criteria results can be seen in Table 21.

Table 21. Criteria results for narrow yield factors.

	Model									
Criteria	1	2	3	4	5	6	7	8	9	10
Average Profit	22.263	19.464	22.562	21.588	23.196	23.472	23.455	23.406	23.152	23.302
Min Profit	13.007	14.782	13.342	16.716	14.671	15.236	16.513	16.430	14.901	16.412
Max Profit	27.484	24.574	27.773	26.665	27.666	28.806	28.614	28.549	27.636	28.831
Regret	- 20.255	- 48.244	- 17.269	- 27.006	- 10.923	- 8.168	- 8.340	- 8.823	- 11.369	- 9.868
Average TTN0	4.35	3.67	4.25	3.72	3.95	3.99	3.74	3.73	3.92	3.77
Max TTN0	4.79	3.95	4.68	3.96	4.28	4.26	3.91	3.91	4.21	3.97
Min TTN0	4.04	3.43	3.94	3.51	3.71	3.77	3.52	3.52	3.72	3.53

Table 22 shows for each criterion, which model performs best.

Table 22. Best performing models per criterion for narrow yield factors.

Criteria	Model
Max Average Profit	6
Max Min Profit	4
Max Max Profit	10
Min Regret Profit	6
Min Average TTN0	2
Min Max TTN0	8
Min Min TTN0	2

A rank-score evaluation method was applied to the results of the method for all seven criteria. This simply sums all the rankings for each facility model for all criteria to yield a total performance score. The lower the score, the better performing the facility model. Table 23 shows the rank-score results for all models against all criteria.

Table 23. Rank-score results for all models against all criteria for narrow yield factors

	Model									
Criteria	1	2	3	4	5	6	7	8	9	10
Average Profit	8	10	7	9	5	1	2	3	6	4
Min Profit	10	7	9	1	8	5	2	3	6	4
Max Profit	8	10	5	9	6	2	3	4	7	1
Regret	8	10	7	9	5	1	2	3	6	4
Average TTN0	10	1	9	2	7	8	4	3	6	5
Max TTN0	10	3	9	4	8	7	2	1	6	5
Min TTN0	10	1	9	2	6	8	3	4	7	5
Total	64	42	55	36	45	32	18	21	44	28

By checking which models are non-dominant per the criteria, we can remove models 1, 3, 5, and 9 from consideration. This allows decision makers to more rigorously evaluate a smaller set of possible facility design solutions, in this case, models 2, 4, 6, 7, 8, and 10.

Table 24. Model 7 production capacity design solution for narrow yield factors (units production capacity).

	Irrigation Recipe Connections														
Lighting Type	*R4*	*R3*	*R4 & R4*	*R2*	*R2 & R4*	*R2 & R3*	*R2 & R3 & R4*	*R1*	*R1 & R4*	*R1 & R3*	*R1 & R3 & R4*	*R1 & R2*	*R1 & R2 & R4*	*R1 & R2 & R3*	*All*
Variety 1	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0
Variety 2	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0
Variety 3	0	0	0	1	0	0	0	7	0	0	0	0	0	0	0
Variety 4	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0
Variety 5	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0
Universal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flexible	0	2	0	1	0	0	0	2	0	0	0	0	0	0	0

Table 25. Summary results for Model 7 solution for narrow yield factors.

Total Cost ($)	27,940,212.79
Total Area (sq.ft.))	40,644.23
Stacks	7
Germination Racking Bays	3
Packaging Lines	1
Seeding Lines	1
Harvest and Cleaning Systems	1
FGI Racking Bays	9
RGI Racking Bays	4
Auxilliary space (ft2)	20,141.73
Bench Handing Systems	1

Table 24 and Table 25 show the specific solution for model 7 as produced from the narrow yield factor method application. As can be seen, this solution suggests building seven stacks of racking (70 layers) into the grow chamber. As an example, per Table 24, 28 layers of the production capacity would be connected to irrigation recipe 3 with a variety 5 specific lighting system, or two layers of the production capacity would be connected to irrigation recipe one with a flexible lighting system.

An evaluation of the expected value of perfect information (EVPI) with respect to demand can be carried out across the DSs applied to the method. Assuming the DSs used sufficiently represent the space of potential demand, the EVPI in this case gives a sense of how much money Company A should consider investing (in market research, business case development, etc.) to determine which DS is most likely to occur. In this case, EVPI is the difference between the expected profit *given* perfect information (EPPI) and the maximum total expected profit (TEP). The TEP for each facility model can be calculated by the dot product of a vector of that model's expected profit for each DS and the probability vector of DS probabilities. Using equally likely probabilities across all DSs (10%), the results of this can be seen in Table 26.

Table 26. Total expected profit (TEP) for each model for narrow yield factors ($mm).

	Model									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
TEP	22.263	19.464	22.562	21.588	23.196	23.472	23.455	23.406	23.152	23.302

In this case, the maximum TEP is that for model 6. EPPI can be calculated as the dot product of the vector of expected profit for each DS if it were known ahead of time that the DS in question would occur, and the probability vector of DS probabilities. The diagonal in Table 18 shows, for each DS, what the expected profit would be if it was certain that each DS occurred. For example, if it was certain that DS1 would occur, company A would build a facility accordingly and expect $27,103,000 in profit over the 10-year period. With these results, EPPI is calculated as $24,288,000. Finally, EVPI is calculated as EPPI – TEP. The EVPI for DSs assuming narrow yield factors is $816,000. That is, assuming the 10 DSs used for the method are a good representation of the possible discrete realities, and that they are equally likely to occur, Company A should spend no more than $816,000 on determining which will happen.

Given "narrow" LFs and RFs, and assuming all IFs = 0, the results of applying the proposed method suggest that a farm profit-optimized for DS7 performs best across all evaluation criteria. Models optimized for both DS6 and DS2 also deserve consideration if the decision makers at company A are specifically concerned about maximizing profit or minimizing TTN0, respectively.

4.2.2. Wide Yield Factor Results

The second application of the proposed method applies the "wide" LFs and RFs and assumes all IFs = 0. The expected profit results of applying the method can be seen in Table 27.

Table 27. Summary results for wide yield factors ($mm).

	Model									
Demand Scenario	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
1	25.882	18.360	24.993	20.594	19.653	24.629	20.850	15.625	15.544	21.176
2	10.121	16.355	12.383	16.152	13.553	13.853	15.929	15.895	13.854	15.948
3	26.046	22.016	27.401	24.183	25.221	26.108	25.185	22.465	21.086	24.896
4	12.589	18.112	14.831	18.507	15.991	16.116	18.298	18.274	16.256	18.261
5	21.669	19.989	23.321	21.967	23.808	22.259	22.487	22.415	22.462	21.901
6	23.941	22.601	24.221	24.088	18.990	27.268	23.281	15.521	15.647	24.145
7	19.134	20.813	21.329	22.426	22.069	21.576	22.926	21.002	20.553	22.430
8	20.349	22.436	22.658	24.376	23.780	22.578	24.526	24.899	23.174	24.290
9	17.338	15.081	18.570	16.796	19.010	17.377	17.181	17.147	19.755	16.388
10	22.962	25.982	25.270	27.886	24.534	26.081	27.478	23.993	20.726	28.346

The TTN0 results of applying the method can be seen in Table 28.

Table 28. TTN0 results for wide yield factors (years).

	Model									
Demand Scenario	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
1	4.66	4.27	4.36	4.15	4.30	4.39	4.11	4.30	4.50	4.22
2	5.49	3.93	4.85	3.98	4.52	4.62	3.99	3.95	4.43	4.01
3	4.40	3.81	4.03	3.75	3.86	4.02	3.70	3.67	4.00	3.76
4	5.25	3.91	4.70	3.91	4.38	4.50	3.92	3.88	4.30	3.95
5	4.64	3.89	4.21	3.81	3.95	4.19	3.78	3.74	3.97	3.85
6	4.61	3.87	4.26	3.84	4.36	4.08	3.86	4.36	4.64	3.85
7	4.92	4.02	4.54	4.00	4.30	4.43	4.00	4.01	4.29	4.04
8	4.66	3.78	4.23	3.73	3.97	4.16	3.72	3.66	3.97	3.75
9	4.84	4.15	4.41	4.06	4.13	4.40	4.00	3.97	4.07	4.11
10	4.56	3.67	4.15	3.62	3.92	4.03	3.64	3.62	4.02	3.63

The regret results of applying the method can be seen in Table 29.

Table 29. Regret criteria results for wide yield factors ($mm)

	Model									
Demand Scenario	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
1	-	- 7.522	- 0.889	- 5.287	- 6.229	- 1.253	- 5.032	-10.257	-10.337	- 4.706
2	- 6.234	-	- 3.972	- 0.203	- 2.802	- 2.503	- 0.426	- 0.460	- 2.502	- 0.407
3	- 1.355	- 5.386	-	- 3.218	- 2.180	- 1.294	- 2.216	- 4.936	- 6.316	- 2.505
4	- 5.918	- 0.395	- 3.676	-	- 2.515	- 2.391	- 0.208	- 0.232	- 2.251	- 0.246
5	- 2.139	- 3.819	- 0.487	- 1.841	-	- 1.549	- 1.321	- 1.393	- 1.346	- 1.907
6	- 3.327	- 4.668	- 3.047	- 3.181	- 8.279	-	- 3.987	-11.747	-11.621	- 3.124
7	- 3.792	- 2.113	- 1.598	- 0.500	- 0.857	- 1.350	-	- 1.924	- 2.373	- 0.496
8	- 4.550	- 2.462	- 2.241	- 0.523	- 1.119	- 2.321	- 0.373	-	- 1.724	- 0.609
9	- 2.417	- 4.674	- 1.185	- 2.959	- 0.745	- 2.378	- 2.573	- 2.608	-	- 3.367
10	- 5.384	- 2.363	- 3.075	- 0.460	- 3.812	- 2.265	- 0.868	- 4.352	- 7.620	-

Criteria results, associated summary results, and a rank-score evaluation can be seen in Table 30, Table 31, and Table 32 respectively.

Table 30. Criteria results for wide yield factors.

	Model									
Criteria	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
Average Profit	20.003	20.174	21.498	21.698	20.661	21.784	21.814	19.724	18.906	21.778
Min Profit	10.121	15.081	12.383	16.152	13.553	13.853	15.929	15.521	13.854	15.948
Max Profit	26.046	25.982	27.401	27.886	25.221	27.268	27.478	24.899	23.174	28.346
Regret	-35.115	-33.403	-20.170	-18.172	-28.538	-17.303	-17.005	-37.910	-46.090	-17.366
Average TTN0	4.80	3.93	4.38	3.88	4.17	4.28	3.87	3.92	4.22	3.92
Max TTN0	5.49	4.27	4.85	4.15	4.52	4.62	4.11	4.36	4.64	4.22
Min TTN0	4.40	3.67	4.03	3.62	3.86	4.02	3.64	3.62	3.97	3.63

Table 31. Best performing models per criterion for wide yield factors.

Criteria	***Model***
Max Average Profit	7
Max Min Profit	4
Max Max Profit	10
Min Regret Profit	7
Min Average TTN0	7
Min Max TTN0	7
Min Min TTN0	8

Table 32. Rank-score results for all models against all criteria for wide yield factors

	Model									
Criteria	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
Average Profit	8	7	5	4	6	2	1	9	10	3
Min Profit	10	5	9	1	8	7	3	4	6	2
Max Profit	6	7	4	2	8	5	3	9	10	1
Regret	8	7	5	4	6	2	1	9	10	3
Average TTN0	10	5	9	2	6	8	1	3	7	4
Max TTN0	10	4	9	2	6	7	1	5	8	3
Min TTN0	10	5	9	2	6	8	4	1	7	3
Total	62	40	50	17	46	39	14	40	58	19

By checking which models are non-dominant per the criteria, we can remove models 1, 2, 3, 5, 6, and 9 from consideration. This allows decision makers to more rigorously evaluate a smaller set of possible facility design solutions, in this case, models 4, 7, 8, and 10.

As with the method application on narrow yield factors, Model 7 performs best. Table 33 and Table 34 show the facility design as generated by the method for DS7.

Table 33. Model 7 production capacity design solution for narrow wide factors (units production capacity).

	Irrigation Recipe Connections														
Lighting Type	*R4*	*R3*	*R4 & R4*	*R2*	*R2 & R4*	*R2 & R3*	*R2 & R3 & R4*	*R1*	*R1 & R4*	*R1 & R3*	*R1 & R3 & R4*	*R1 & R2*	*R1 & R2 & R4*	*R1 & R2 & R3*	*All*
Variety 1	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0
Variety 2	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0
Variety 3	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0
Variety 4	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0
Variety 5	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0
Universal	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Flexible	0	0	0	1	0	2	0	3	0	0	0	3	0	0	0

Table 34. Summary results for Model 7 solution for narrow wide factors.

Total Cost ($)	28,649,493.80
Total Area (sq.ft.)	41,019.33
Stacks	7
Germination Racking Bays	3
Packaging Lines	1
Seeding Lines	1
Harvest and Cleaning Systems	1
FGI Racking Bays	9
RGI Racking Bays	4
Auxilliary Space (ft2)	20,516.83
Bench Handling Systems	1

This design solution would have the same number of grow chamber racking stacks, germination racking bays, packaging lines, etc. as that designed by the method for narrow yield factors. The principal difference in this design is how the production capacity is outfitted with different production technology - lighting systems and irrigation recipe connections. As an example, the solution for model 7 for wide yield factors would have 14 racking layers with a connection to irrigation recipe 2 and variety 4 specific lighting, whereas the solution for narrow yield factors would have 18 such layers.

Applying the same per-DS probability (10%) as for the solution for narrow yield factors, TEP for each facility can be seen in Table 35.

Table 35. Total expected profit (TEP) for each model for wide yield factors ($mm).

	Model									
	1	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
TEP	20.003	20.174	21.498	21.698	20.661	21.784	21.814	19.724	18.906	21.778

As can be seen, the maximum TEP is that for model 7. Similarly, EPPI is calculated as $23,003,000. Therefor, the EVPI for DSs using wide yield factors is $1,700,000. This is almost double the EVPI of $816,000 for narrow yield factors. Intuitively, this makes sense – wider yield factors mean there is a greater difference in how different combinations of production capacity technologies produce the different varieties. Conversely, a reality with more narrow yield factors means that the same variety can be produced reasonably well on a range of different production capacity technology combinations. As such an optimal facility design, considering narrow yield factors, could make use of less expensive production capacity, and the difference between optimal designs, DS to DS, would be less then that with wide yield factors. This results in the value of knowing what DS to expect being higher, in a reality with wide yield factors, as opposed to narrow. This result further confirms the method is working appropriately.

4.3. RESULTS 2 – DIFFERENT YIELD FACTORS

To evaluate how much different yield factors effect the output, a second application of the method was devised, optimizing for total profit for a single DS across a range of yield factors. Six different yield factor scenarios were developed as the combinations of three different options for each of the primary yield factors (LF and RF) and two different options for the IFs. Both the LF and RF options are meant to capture three different general realities:

- Option 1. Minimal difference between technologies – all systems/recipes perform well for all varieties
- Option 2. Major difference between technologies – all variety-specific systems/recipes perform well for their specific variety and poorly otherwise.
- Option 3. All variety specific systems/recipe perform well for their specific variety and randomly otherwise (universal systems/recipes perform randomly between moderate and well).

Table 36 to Table 38 outline the three different LF options, Table 39 to Table 41 outline the three different RF options.

Table 36. Lighting system yield factor option 1 (LF1)

	Lighting System						
Variety	***Variety 1***	***Variety 2***	***Variety 3***	***Variety 4***	***Variety 5***	***Universal***	***Flexible***
1	1	0.88	0.92	0.95	0.88	0.86	1
2	0.93	1	0.85	0.91	0.92	0.88	1
3	0.92	0.91	1	0.95	0.88	0.89	1
4	0.85	0.92	0.91	1	0.94	0.9	1
5	0.89	0.93	0.87	0.88	1	0.88	1

Table 37. Lighting system yield factor option 2 (LF2)

	Lighting System						
Variety	***Variety 1***	***Variety 2***	***Variety 3***	***Variety 4***	***Variety 5***	***Universal***	***Flexible***
1	1	0.26	0.23	0.41	0.29	0.67	1
2	0.28	1	0.33	0.42	0.37	0.73	1
3	0.5	0.28	1	0.45	0.31	0.5	1
4	0.44	0.45	0.28	1	0.48	0.61	1
5	0.21	0.48	0.28	0.42	1	0.51	1

Table 38. Lighting system yield factor option 3 (LF3)

	Lighting System						
Variety	***Variety 1***	***Variety 2***	***Variety 3***	***Variety 4***	***Variety 5***	***Universal***	***Flexible***
1	1	0.75	0.95	0.65	0.29	0.59	1
2	0.32	1	0.86	0.54	0.89	0.71	1
3	0.68	0.32	1	0.95	0.28	0.92	1
4	0.42	0.99	0.6	1	0.21	0.95	1
5	0.95	0.63	0.98	0.67	1	0.7	1

Table 39. Nutrient recipe yield factor option 1 (RF1)

	Nutrient Recipe			
Variety	***Recipe 1***	***Recipe 2***	***Recipe 3***	***Recipe 4***
1	1	0.92	0.92	0.91
2	1	0.85	0.87	0.94
3	1	0.93	0.89	0.88
4	0.85	1	0.93	0.94
5	0.89	0.89	1	0.91

Table 40. Nutrient recipe yield factor option 2 (RF2)

	Nutrient Recipe			
Variety	***Recipe 1***	***Recipe 2***	***Recipe 3***	***Recipe 4***
1	1	0.38	0.24	0.71
2	1	0.34	0.31	0.68
3	1	0.43	0.44	0.58
4	0.33	1	0.47	0.7
5	0.33	0.23	1	0.65

Table 41. Nutrient recipe yield factor option 3 (RF3)

	Nutrient Recipe			
Variety	**Recipe 1**	**Recipe 2**	**Recipe 3**	**Recipe 4**
1	1	0.94	0.93	0.24
2	1	0.64	0.31	0.35
3	1	0.29	0.89	0.8
4	0.88	1	0.7	0.9
5	0.2	0.51	1	0.39

For the IFs, the different options are meant to capture two different realities:

- Option 1. Yield factor interaction effect option 1 (IF1) – no interaction effect. All IFs (across all varieties, lighting systems, and nutrient recipes) are equal to 1.
- Option 2. Yield factor interaction effect option 2 (IF2) – random effect. All IFs are randomly generated between 0.9 (10% negative effect) and 1.1 (10% positive effect).

Table 42 and Table 43 outline the two different IF options.

Table 42. Yield factor interaction effect option 1 (IF1)

		Nutrient Recipe			
Variety	***Lighting System Type***	***Recipe 1***	***Recipe 2***	***Recipe 3***	***Recipe 4***
1	***Variety 1***	1	1	1	1
1	***Variety 2***	1	1	1	1
1	***Variety 3***	1	1	1	1
1	***Variety 4***	1	1	1	1
1	***Variety 5***	1	1	1	1
1	***Universal***	1	1	1	1
1	***Flexible***	1	1	1	1
2	***Variety 1***	1	1	1	1
2	***Variety 2***	1	1	1	1
2	***Variety 3***	1	1	1	1
2	***Variety 4***	1	1	1	1
2	***Variety 5***	1	1	1	1
2	***Universal***	1	1	1	1
2	***Flexible***	1	1	1	1
3	***Variety 1***	1	1	1	1
3	***Variety 2***	1	1	1	1
3	***Variety 3***	1	1	1	1
3	***Variety 4***	1	1	1	1
3	***Variety 5***	1	1	1	1
3	***Universal***	1	1	1	1
3	***Flexible***	1	1	1	1
4	***Variety 1***	1	1	1	1
4	***Variety 2***	1	1	1	1
4	***Variety 3***	1	1	1	1
4	***Variety 4***	1	1	1	1
4	***Variety 5***	1	1	1	1
4	***Universal***	1	1	1	1
4	***Flexible***	1	1	1	1
5	***Variety 1***	1	1	1	1
5	***Variety 2***	1	1	1	1
5	***Variety 3***	1	1	1	1
5	***Variety 4***	1	1	1	1
5	***Variety 5***	1	1	1	1
5	***Universal***	1	1	1	1
5	***Flexible***	1	1	1	1

Table 43. Yield factor interaction effect option 2 (IF2)

		Nutrient Recipe			
Variety	***Lighting System Type***	***Recipe 1***	***Recipe 2***	***Recipe 3***	***Recipe 4***
1	***Variety 1***	1.03	0.95	1.08	0.9
1	***Variety 2***	0.95	0.99	1.09	0.97
1	***Variety 3***	0.98	1.03	0.94	1.04
1	***Variety 4***	1.02	0.98	1	1
1	***Variety 5***	0.95	1.02	1	1.04
1	***Universal***	0.95	1.01	0.98	1.05
1	***Flexible***	1.05	0.9	0.97	1
2	***Variety 1***	1.08	0.96	0.9	1.06
2	***Variety 2***	0.96	1.06	0.93	0.91
2	***Variety 3***	1	1.1	0.96	1.03
2	***Variety 4***	1.05	0.9	0.94	0.94
2	***Variety 5***	0.94	0.94	1.02	1.08
2	***Universal***	0.97	1.05	0.9	1.02
2	***Flexible***	0.99	0.97	0.94	1
3	***Variety 1***	0.99	0.99	0.95	1
3	***Variety 2***	0.93	1.07	1.07	0.99
3	***Variety 3***	0.92	0.9	1.07	0.96
3	***Variety 4***	0.98	0.94	1.04	0.94
3	***Variety 5***	1.04	1.03	1.08	1.03
3	***Universal***	1.06	0.99	0.94	1.09
3	***Flexible***	0.98	0.92	0.94	0.96
4	***Variety 1***	1.05	1.1	1.09	0.96
4	***Variety 2***	0.95	0.9	1	0.92
4	***Variety 3***	1.04	1.02	0.9	0.98
4	***Variety 4***	1.06	1.03	1.07	0.92
4	***Variety 5***	1.08	0.98	1.08	1.05
4	***Universal***	1.02	0.99	1.05	1.05
4	***Flexible***	1.1	1.08	0.92	1.08
5	***Variety 1***	1.06	0.92	0.93	1.05
5	***Variety 2***	0.99	0.95	0.94	1
5	***Variety 3***	0.9	0.99	0.92	0.9
5	***Variety 4***	0.94	1.03	1.1	1.07
5	***Variety 5***	0.91	0.94	0.9	1.1
5	***Universal***	0.97	0.99	0.99	0.92
5	***Flexible***	1.08	1.03	0.96	1.07

The yield factor options have been combined to generate 6 different scenarios as outlined in Table 44.

Table 44. List of different yield factor scenarios based on primary and interaction yield factor options.

Scenario	*Lighting Factor Option*	*Nutrient Recipe Factor Option*	*Interaction Factor Option*
1	LF1	RF1	IF1
2	LF1	RF1	IF2
3	LF2	RF2	IF1
4	LF2	RF2	IF2
5	LF3	RF3	IF1
6	LF3	RF3	IF2

After consulting horticultural experts both internal and external to GoodLeaf, these 6 different yield factor scenarios have been determined a simple and effective representation of the potential set of effects. Scenarios 1 and 2 represent the reality where the primary factors, and associated technologies, have a minor effect on overall yield (all plants grow well regardless of production technology) and the interaction effect is present or not respectively. Scenarios 3 and 4 represent the reality where the primary factors have a major effect on overall yield (plants grown not using their specific production capacity, or flexible capacity, do not grow well) and the interaction effect is present or not respectively. Scenarios 5 and 6 represent the reality where the primary factors have some effect, but plants not grown using their specific production capacity (or flexible capacity) have a random chance of performing well, and the interaction effect is present or not respectively.

Using these six different yield factor scenarios, the method was applied to five of the DSs as outlined in the previous section – DS3 (random annual increase), DS6 (randomly consistent with high variance), DS8 (randomly consistent with low variance), DS9 (random annual increase for varieties 4 and 5, random annual decrease for varieties 1, 2, and 3) and DS10 (random annual decrease for varieties 4 and 5, random annual increase for varieties 1, 2, and 3). For each application, the results have been analyzed against the same seven criteria as outlined in the previous section – for a given DS, this provides decision makers with a set of potential farm designs, each optimized for one of the six yield factor scenarios, and different measures of how they perform. We will explore the results for DS3 in detail and the results for DS6, DS8, DS9, and DS10 can be found in Appendix A.

4.3.1. Demand Scenario 3.

The expected profit results for applying the modified method to DS3 can be seen in Table 45.

Table 45. Summary results for DS3 ($mm).

	Model					
Yield Factor Scenario	***1***	***2***	***3***	***4***	***5***	***6***
1	27.946	25.793	27.472	26.601	27.550	26.830
2	26.448	28.713	26.368	26.877	26.472	27.452
3	20.653	9.583	27.374	26.337	20.392	22.597
4	17.579	11.479	25.859	26.718	18.298	22.932
5	26.931	11.973	27.413	26.533	27.719	26.926
6	25.352	13.727	25.883	26.784	26.180	27.259

As an example of the meaning of the results in table 43 – column 1, row 3 is showing, for DS3, the expected profit of a facility optimally designed for yield factor scenario 1 (LF1, RF1, and IF1) operating in a reality where yield factor scenario 3 (LF2, RF2, IF1) is realized.

Similarly, TTN0 and regret results for the application of the modified method to DS3 can be seen in Table 46 and Table 47.

Table 46. TTNO results for DS3 (years).

	Model					
Yield Factor Scenario	***1***	***2***	***3***	***4***	***5***	***6***
1	3.73	3.92	4.03	4.17	3.76	3.88
2	3.81	3.70	4.08	4.14	3.83	3.81
3	4.13	5.99	4.03	4.18	4.29	4.14
4	4.41	5.53	4.09	4.15	4.49	4.05
5	3.79	5.71	4.03	4.17	3.76	3.88
6	3.84	5.37	4.09	4.14	3.82	3.81

Table 47. Regret results for DS3 ($mm)

	Model					
Scenario	**1**	**2**	**3**	**4**	**5**	**6**
1	-	- 2.154	- 0.475	- 1.345	- 0.396	- 1.117
2	- 2.265	-	- 2.345	- 1.837	- 2.241	- 1.261
3	- 6.721	-17.790	-	- 1.037	- 6.982	- 4.777
4	- 9.139	-15.239	- 0.859	-	- 8.420	- 3.786
5	- 0.788	-15.746	- 0.306	- 1.186	-	- 0.793
6	- 1.907	-13.532	- 1.376	- 0.476	- 1.080	-

The seven-criteria analysis results, criteria summary results, and rank-score evaluation results can be seen in Table 48, Table 49, and Table 50 respectively.

Table 48. Criteria results for DS3

	Model					
Criteria	***1***	***2***	***3***	***4***	***5***	***6***
Average Profit	24.152	16.878	26.728	26.642	24.435	25.666
Min Profit	17.579	9.583	25.859	26.337	18.298	22.597
Max Profit	27.946	28.713	27.472	26.877	27.719	27.452
Regret	-20.820	-64.461	- 5.361	- 5.880	-19.118	-11.733
Average TTN0	3.95	5.04	4.06	4.16	3.99	3.93
Max TTN0	4.41	5.99	4.09	4.18	4.49	4.14
Min TTN0	3.73	3.70	4.03	4.14	3.76	3.81

Table 49. Best performing models per criterion for DS3.

Criteria	***Model***
Max Average Profit	3
Max Min Profit	4
Max Max Profit	2
Min Regret Profit	3
Min Average TTN0	6
Min Max TTN0	3
Min Min TTN0	2

Table 50. Rank-score results for all models against all criteria for DS3.

	Model					
	1	**2**	**3**	**4**	**5**	**6**
Average Profit	5	6	1	2	4	3
Min Profit	5	6	2	1	4	3
Max Profit	2	1	4	6	3	5
Regret	5	6	1	2	4	3
Average TTN0	2	6	4	5	3	1
Max TTN0	4	6	1	3	5	2
Min TTN0	2	1	5	6	3	4
Total	25	32	18	25	26	21

Checking for dominant solutions according to the criteria, none of the models are dominant. By the rank-score evaluation, models 3 and 6 should be considered. That is, if decision makers assume that DS3 will occur, but yield factors are still unknown, a facility should be designed with yield factor scenario 3 (LF2, RF2, IF1) in mind. Comparing the performance of Models 2 (the worst option per the analysis) and 3, it can be verified that the method is working as expected. Model 2, designed for yield factor scenario 2, generally assumes that all varieties perform well on all possible production capacities. Model 3, designed for yield factor scenario 3, generally assumes that all varieties only perform well on production capacities designed for them (or designed flexibly). It would be expected that a system designed as Model 2 would not perform well in a reality such as yield factor scenario 3. This is precisely what is modelled by the method. In table 42, Model 2 performs very poorly if applied to yield factor scenario 3. Conversely, the opposite is true. It would be expected that a system design as Model 3 would perform well in a reality such as yield factor scenario 2. Again, this is precisely what is modelled by the method.

An EVPI analysis was performed, this time with an equally likely per-yield factor scenario probability of 16.67%. TEP for each facility can be seen in Table 51.

Table 51. Total expected profit (TEP) for each model for DS3 ($).

	Model					
	1	**2**	**3**	**4**	**5**	**6**
TEP	24.152	16.878	26.728	26.642	24.435	25.666

The maximum TEP is that for model 3. EPPI is calculated as $27,621,000. Therefor the EVPI for yield factors is $893,000. That is, for this example organization, if the assumption is that DS3 will occur and all yield factor scenarios are equally likely, the value of determining exactly which yield factor scenario is reality is $893,000. This is the maximum that the organization should consider spending on research and development efforts to determine the true yield factors.

Table 52 shows a summary of the results for apply the method to DS3, DS6, DS8, DS9, and DS10. Full results (as above) for DS6, DS8, DS9, DS10 can be seen in appendix A.

Table 52. Summary results for method application, for unknown yield factors, against demand scenarios 3, 6, 8, 9, and 10.

Demand Scenario	*Best Rank-Score*	*Expected Profit ($mm)*	*Facility CAPEX ($mm)*	*EVPI ($mm)*
DS3	Model 3	26.728	33.109	0.893
DS6	Model 1	25.917	30.476	0.887
DS8	Model 3	23.739	28.299	1.006
DS9	Model 3	19.215	30.519	0.894
DS10	Model 3	27.836	28.811	0.855

5. CONCLUSIONS

5.1. CONTRIBUTIONS

The proposed decision-making tool and method helps provide additional context to VF firm business leaders in a burgeoning industry with a distinct lack of operational and economic standards and a high level of uncertainty. Further, this work and data contributes to the literature and research on modelling business risk and uncertainty in the VF industry.

The method as developed through this research and presented in this thesis makes use of two sequential MILP models to provide a decision-making tool for firms operating in the indoor vertical farming industry. It helps determine how to best size and outfit a new commercial VF production facility, considering the uncertain effect of different production capacity configurations and uncertain demand for products. Though decision support systems and tools exist in the literature for site selection, product portfolio development, and facility size, consideration of different production technology combinations is unique to this study. Typically, the literature associated with flexible production technology considers different production systems to either be capable or incapable of producing a given product. This research suggests a technique, specifically applied to horticultural lighting and irrigation nutrient systems, for modelling varying output effects of different production combinations for distinct products. The output of the method is a menu of production capacity configurations and measures of how they perform against pre-selected criteria. It also provides a high-level, per-period, production plan considering the capacity configuration selected. For verification purposes, the method has been applied to a case study of a VF firm looking to expand its operations, using a range of different potential lighting and irrigation capacity configurations, their effect on production and associated uncertainty, and a range of potential demand scenarios.

Finally, the method can be used to evaluate the EVPI associated with the production technology efficacy and demand uncertainty, potentially setting a funding benchmark for exploring either. As can be seen in Figure 3, the results of the wide range of production technology effects and demand scenarios used in the case study to verify the method suggest that the, for a given new production facility, the EVPI for production system yield factors is in the range of 2.5% - 3.5% of the total CAPEX of the facility. Similarly, as depicted in Figure 4, the EVPI for demand is in the range of 3% - 6%.

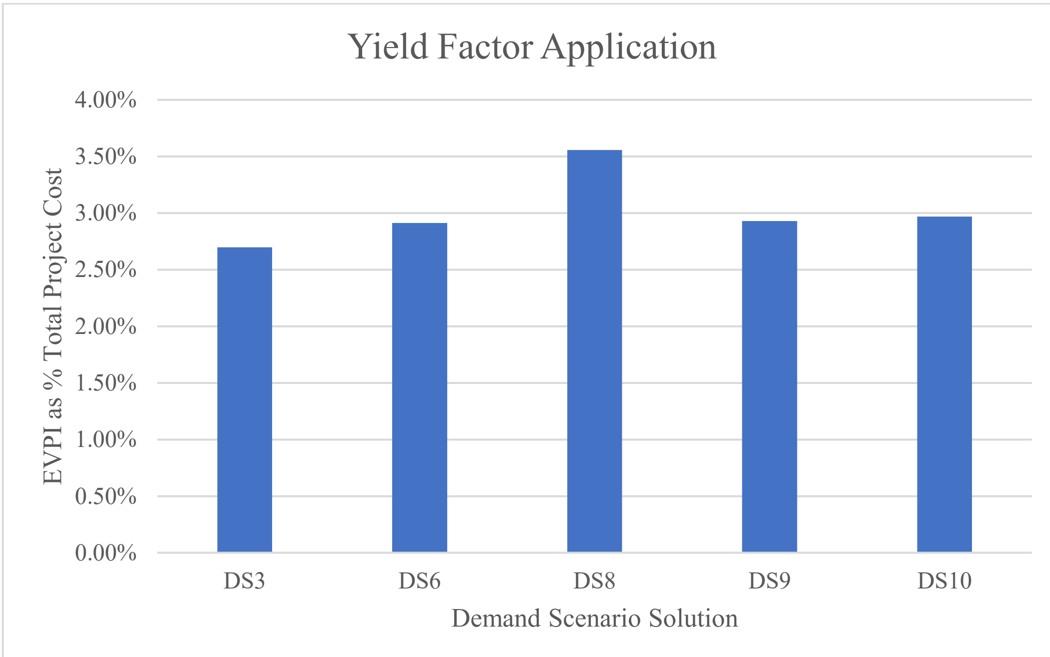

Figure 3. Yield factor EVPI as a percentage of total facility CAPEX.

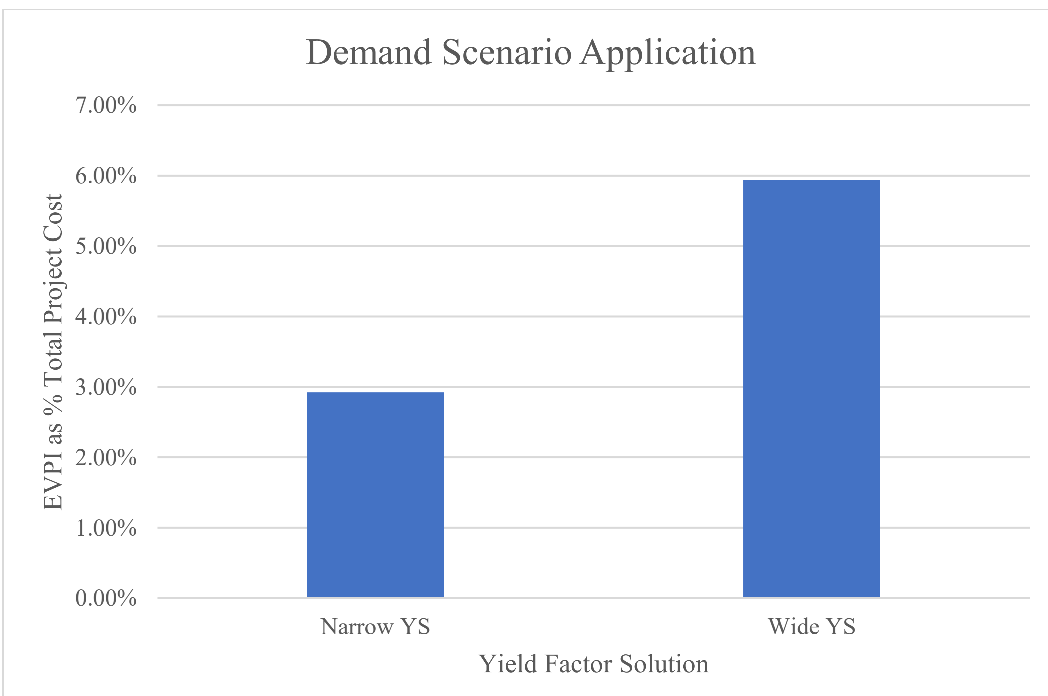

Figure 4. Demand scenario EVPI as a percentage of total facility CAPEX.

5.2. IMPROVEMENT AND FURTHER RESEARCH

The method as developed has some limitations and could be extended and further explored in three main ways: evaluation, expansion, and refinement. In terms of evaluation, the method should be applied to a wider and deeper range of inputs and parameters through different case studies to further explore its dynamics. These more comprehensive inputs and parameters are:

- More granular time periods. As tested, the method is applied to annual demand and production periods. Monthly, or weekly periods should be tested.
- More sophisticated DS modelling. Rather than a set of different DSs, a dynamic DS modelling module could be developed, using market data and more subject matter expert input, to generate new DSs per method application. The method could then be applied at a much larger scale for aggregate results.
- More advanced and/or more accurate growing system effect modelling. Though the modelling technique used herein is satisfactory given the lack of a specific and detailed function representing the response of different crops to their associated inputs, as this is better researched, these inputs should be updated accordingly.

The method could also be expanded and generalized to encompass more details specific to a given case. For instance, it could also incorporate different climate setpoints as a third dimension of production technology – perhaps modelled as distinct parts of a segmented grow chamber. The method could also extend beyond a single facility, solving for a network of facilities - their respective locations, product portfolios and market supply, considering location-specific property, energy, and supply chain costs. For instance, it may be optimal to have a network of product-specific production facilities rather than a network of individual facilities each producing all products. Further, certain products may require more energy input than others – it may be optimal to produce high-energy in low-cost energy locations and vice-versa.

From a generalizability standpoint, the concept of the method as a capital investment/allocation evaluation tool given investment efficacy uncertainty and investment requirement uncertainty using the principals of stochastic programming and robust optimization could be applied to any firm in any industry experiencing similar challenges, such as being a fledgling large-scale manufacturer in a new and evolving market.

The method as developed optimizes for total profit over the demand planning horizon. The results of these solutions are then analyzed against the criteria as discussed. With further research a standard set of criteria could be developed that best apply to the industry. Further, the criteria themselves could be ranked/scored and then incorporated into the MILP formulation as a multi-objective MILP for more exact solutions.

This work has developed and proven the efficacy of a model which could be used to evaluate real-world cases. Given the theoretical nature of this research and the application of the method to a specific case study, we cannot make generalized conclusions about vertical farming business models (e.g., it is best to build highly flexible production capacity), as the suggested path forward is highly dependent on the situation and associated inputs. The following areas have been identified for further research:

- Operational and manufacturing engineering associated with the indoor vertical farming industry. As the industry matures, production methods are focused, and will continue to focus, on a few key processes. These processes should be researched, evaluated, improved, and standardized.
- Economic and financial characteristics of the indoor VF industry and its future., including industry data collection, reporting, and market dynamics.
- Demand forecasting for current and future products produced by VF production systems.
- In-depth horticultural research on growth response functions for common cultivars used in the indoor VF industry, specifically understanding the dynamics of how yield/quality are affected by combinations of differing light, nutrient, and climate inputs. Using the structure of the method in this study, experiments could be developed to properly determine the value of reducing uncertainty in LFs, RFs, and IFs.

APPENDIX A. FURTHER RESULTS FOR SECTION 4.3

DEMAND SCENARIO 6

Table 53. Summary results for DS6 ($mm).

	Model					
Yield Factor Scenario	***1***	***2***	***3***	***4***	***5***	***6***
1	28.882	27.233	28.106	27.276	28.415	27.569
2	28.073	29.571	27.826	27.521	28.084	28.036
3	23.872	10.484	27.267	26.648	17.308	17.425
4	22.153	11.865	26.265	26.841	16.498	17.451
5	27.254	14.962	27.291	27.133	28.397	27.727
6	25.267	16.612	26.340	27.393	27.632	28.175

Table 54. TTN0 results for DS6 (years).

	Model					
Yield Factor Scenario	***1***	***2***	***3***	***4***	***5***	***6***
1	3.87	3.88	3.98	4.13	3.91	4.01
2	3.92	3.71	4.00	4.10	3.94	3.98
3	3.97	5.64	3.99	4.16	4.73	5.10
4	4.12	5.38	4.08	4.13	4.87	5.14
5	3.89	5.41	3.99	4.13	3.90	3.99
6	4.01	5.11	4.08	4.10	3.92	3.95

Table 55. Regret results for DS6 ($mm).

	Model					
Scenario	**1**	**2**	**3**	**4**	**5**	**6**
1	-	- 1.649	- 0.776	- 1.605	- 0.466	- 1.312
2	- 1.498	-	- 1.745	- 2.050	- 1.487	- 1.535
3	- 3.395	- 16.782	-	- 0.618	- 9.959	- 9.842
4	- 4.689	- 14.976	- 0.576	-	- 10.344	- 9.390
5	- 1.143	- 13.435	- 1.106	- 1.265	-	- 0.670
6	- 2.907	- 11.562	- 1.835	- 0.782	- 0.542	-

Table 56. Criteria results for DS6.

	Model					
Criteria	***1***	***2***	***3***	***4***	***5***	***6***
Average Profit	25.917	18.455	27.182	27.135	24.389	24.397
Min Profit	22.153	10.484	26.265	26.648	16.498	17.425
Max Profit	28.882	29.571	28.106	27.521	28.415	28.175
Regret	- 13.633	- 58.404	- 6.039	- 6.320	- 22.799	- 22.750
Average TTN0	3.96	4.85	4.02	4.12	4.21	4.36
Max TTN0	4.12	5.64	4.08	4.16	4.87	5.14
Min TTN0	3.87	3.71	3.98	4.10	3.90	3.95

Table 57. Best performing model per criterion for DS6.

Criteria	***Model***
Max Average Profit	3
Max Min Profit	4
Max Max Profit	2
Min Regret Profit	3
Min Average TTN0	1
Min Max TTN0	3
Min Min TTN0	2

Table 58. Rank-score results for all models against all criteria for DS6.

	Model					
	1	2	3	4	5	6
Average Profit	3	6	1	2	5	4
Min Profit	3	6	2	1	5	4
Max Profit	2	1	5	6	3	4
Regret	3	6	1	2	5	4
Average TTN0	1	6	2	3	4	5
Max TTN0	2	6	1	3	4	5
Min TTN0	2	1	5	6	3	4
Total	16	32	17	23	29	30

Table 59. TEP for all models for DS6 ($mm).

	Model					
	1	2	3	4	5	6
TEP	23.405	15.699	23.739	24.127	23.265	22.999

Demand Scenario 8

Table 60. Summary results for DS8 ($mm).

	Model					
Yield Factor Scenario	1	2	3	4	5	6
1	25.111	23.128	24.809	23.948	25.184	23.977
2	23.454	25.814	22.893	24.343	23.304	24.565
3	24.024	12.104	24.884	23.748	23.823	20.738
4	20.184	13.707	22.411	24.399	19.540	20.189
5	25.128	8.925	24.902	23.924	25.149	23.794
6	22.528	10.515	22.535	24.401	22.588	24.730

Table 61. TTN0 results for DS8 (years).

	Model					
Yield Factor Scenario	1	2	3	4	5	6
1	3.62	3.83	3.67	3.80	3.60	3.78
2	3.76	3.58	3.85	3.76	3.77	3.72
3	3.73	5.37	3.66	3.83	3.73	4.12
4	4.10	5.06	3.89	3.76	4.18	4.18
5	3.61	6.04	3.66	3.81	3.61	3.81
6	3.86	5.67	3.88	3.76	3.84	3.70

Table 62. Regret results for DS8 ($mm).

	Model					
Scenario	**1**	**2**	**3**	**4**	**5**	**6**
1	-	- 1.983	- 0.302	- 1.163	0.072	- 1.135
2	- 2.361	-	- 2.921	- 1.471	- 2.511	- 1.249
3	- 0.859	- 12.780	-	- 1.136	- 1.061	- 4.146
4	- 4.216	- 10.692	- 1.988	-	- 4.859	- 4.210
5	- 0.021	- 16.224	- 0.247	- 1.225	-	- 1.355
6	- 2.202	- 14.215	- 2.195	- 0.329	- 2.142	-

Table 63. Criteria results for DS8.

	Model					
Criteria	***1***	***2***	***3***	***4***	***5***	***6***
Average Profit	23.405	15.699	23.739	24.127	23.265	22.999
Min Profit	20.184	8.925	22.411	23.748	19.540	20.189
Max Profit	25.128	25.814	24.902	24.401	25.184	24.730
Regret	- 9.659	- 55.894	- 7.654	- 5.324	- 10.501	- 12.095
Average TTN0	3.78	4.93	3.77	3.79	3.79	3.88
Max TTN0	4.10	6.04	3.89	3.83	4.18	4.18
Min TTN0	3.61	3.58	3.66	3.76	3.60	3.70

Table 64. Best performing model per criterion for DS8

Criteria	***Model***
Max Average Profit	4
Max Min Profit	4
Max Max Profit	2
Min Regret Profit	4
Min Average TTN0	3
Min Max TTN0	4
Min Min TTN0	2

Table 65. Rank-Score Results for all models against all criteria for DS8.

	Model					
	1	2	3	4	5	6
Average Profit	3	6	2	1	4	5
Min Profit	4	6	2	1	5	3
Max Profit	3	1	4	6	2	5
Regret	3	6	2	1	4	5
Average TTN0	2	6	1	3	4	5
Max TTN0	3	6	2	1	5	4
Min TTN0	3	1	4	6	2	5
Total	21	32	17	19	26	32

Table 66. TEP for all models for DS8 ($mm).

	Model					
	1	2	3	4	5	6
TEP	25.917	18.455	27.182	27.135	24.389	24.397

Demand Scenario 9

Table 67. Summary results for DS9 ($mm).

	Model					
Yield Factor Scenario	1	2	3	4	5	6
1	20.461	18.436	20.063	19.162	20.226	19.380
2	19.231	21.056	18.696	19.392	19.035	19.728
3	17.824	3.536	19.885	18.763	16.985	15.981
4	15.266	5.965	18.123	19.138	14.839	16.092
5	19.860	3.040	20.115	19.060	20.356	19.397
6	18.312	4.965	18.408	19.319	19.001	19.760

Table 68. TTN0 results for DS9 (years).

	Model					
Yield Factor Scenario	1	2	3	4	5	6
1	3.93	4.13	4.02	4.21	3.93	4.10
2	4.00	3.93	4.13	4.20	4.00	4.06
3	4.29	7.66	4.05	4.28	4.24	4.50
4	4.63	6.75	4.21	4.24	4.50	4.46
5	3.97	7.74	4.01	4.22	3.93	4.11
6	4.07	6.87	4.15	4.20	4.00	4.06

Table 69. Regret results for DS9 ($mm).

	Model					
Scenario	**1**	**2**	**3**	**4**	**5**	**6**
1	-	- 2.025	- 0.397	- 1.298	- 0.234	- 1.081
2	- 1.826	-	- 2.360	- 1.664	- 2.022	- 1.328
3	- 2.060	- 16.349	-	- 1.122	- 2.899	- 3.904
4	- 3.871	- 13.173	- 1.015	-	- 4.299	- 3.046
5	- 0.496	- 17.316	- 0.241	- 1.295	-	- 0.959
6	- 1.448	- 14.795	- 1.353	- 0.441	- 0.759	-

Table 70. Criteria results for DS9.

	Model					
Criteria	***1***	***2***	***3***	***4***	***5***	***6***
Average Profit	18.492	9.499	19.215	19.139	18.407	18.390
Min Profit	15.266	3.040	18.123	18.763	14.839	15.981
Max Profit	20.461	21.056	20.115	19.392	20.356	19.760
Regret	- 9.701	- 63.658	- 5.365	- 5.820	- 10.213	- 10.318
Average TTN0	4.15	6.18	4.09	4.22	4.10	4.21
Max TTN0	4.63	7.74	4.21	4.28	4.50	4.50
Min TTN0	3.93	3.93	4.01	4.20	3.93	4.06

Table 71. Best performing model per criterion for DS9.

Criteria	***Model***
Max Average Profit	3
Max Min Profit	4
Max Max Profit	2
Min Regret Profit	3
Min Average TTN0	3
Min Max TTN0	3
Min Min TTN0	1

Table 72. Rank-score results for all models against all criteria for DS9.

	Model					
	1	2	3	4	5	6
Average Profit	3	6	1	2	4	5
Min Profit	4	6	2	1	5	3
Max Profit	2	1	4	6	3	5
Regret	3	6	1	2	4	5
Average TTN0	3	6	1	5	2	4
Max TTN0	5	6	1	2	3	4
Min TTN0	1	3	4	6	2	5
Total	21	34	14	24	23	31

Table 73. TEP for all models for DS9 ($mm).

	Model					
	1	2	3	4	5	6
TEP	18.492	9.499	19.215	19.139	18.407	18.390

DEMAND SCENARIO 10

Table 74. Summary results for DS10 ($mm).

	Model					
Yield Factor Scenario	1	2	3	4	5	6
1	28.920	27.228	28.434	27.642	28.679	27.892
2	27.887	29.404	27.415	28.060	27.751	28.499
3	23.163	13.774	28.413	27.519	21.334	22.448
4	20.429	14.795	27.134	27.905	19.937	22.146
5	28.218	17.357	28.415	27.625	28.901	28.033
6	26.691	18.898	27.206	28.048	27.759	28.605

Table 75. TTN0 results for DS10 (years).

	Model					
Yield Factor Scenario	1	2	3	4	5	6
1	3.52	3.73	3.62	3.74	3.55	3.68
2	3.64	3.50	3.74	3.69	3.67	3.61
3	3.72	5.39	3.63	3.76	4.10	4.17
4	3.99	5.16	3.77	3.70	4.26	4.19
5	3.54	4.93	3.62	3.74	3.53	3.67
6	3.68	4.71	3.76	3.70	3.67	3.60

Table 76. Regret results for DS10 ($mm).

	Model					
Scenario	**1**	**2**	**3**	**4**	**5**	**6**
1	-	- 1.692	- 0.486	- 1.278	- 0.241	- 1.028
2	- 1.517	-	- 1.989	- 1.344	- 1.653	- 0.905
3	- 5.250	- 14.638	-	- 0.893	- 7.078	- 5.965
4	- 7.476	- 13.110	- 0.771	-	- 7.968	- 5.759
5	- 0.683	- 11.544	- 0.486	- 1.276	-	- 0.868
6	- 1.914	- 9.708	- 1.399	- 0.557	- 0.846	-

Table 77. Criteria results for DS10.

	Model					
Criteria	***1***	***2***	***3***	***4***	***5***	***6***
Average Profit	25.885	20.243	27.836	27.800	25.727	26.270
Min Profit	20.429	13.774	27.134	27.519	19.937	22.146
Max Profit	28.920	29.404	28.434	28.060	28.901	28.605
Regret	- 16.839	- 50.692	- 5.131	- 5.348	- 17.786	- 14.525
Average TTN0	3.68	4.57	3.69	3.72	3.80	3.82
Max TTN0	3.99	5.39	3.77	3.76	4.26	4.19
Min TTN0	3.52	3.50	3.62	3.69	3.53	3.60

Table 78. Best performing model per criterion for DS10.

Criteria	***Model***
Max Average Profit	3
Max Min Profit	4
Max Max Profit	2
Min Regret Profit	3
Min Average TTN0	1
Min Max TTN0	4
Min Min TTN0	2

Table 79. Rank-score results for all models against all criteria for DS10.

	Model					
	1	2	3	4	5	6
Average Profit	4	6	1	2	5	3
Min Profit	4	6	2	1	5	3
Max Profit	2	1	5	6	3	4
Regret	4	6	1	2	5	3
Average TTN0	1	6	2	3	4	5
Max TTN0	3	6	2	1	5	4
Min TTN0	2	1	5	6	3	4
Total	20	32	18	21	30	26

Table 80. TEP for all models for DS10 ($mm).

	Model					
	1	2	3	4	5	6
TEP	25.885	20.243	27.836	27.800	25.727	26.270

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