A DECISION MODEL FOR RESOURCE MANAGEMENT
USING RULE-BASED UTILITY FUNCTIONS AND
PARAMETER SELECTION

A DISSERTATION

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by

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DEDICATION

This work is dedicated

to

Gillian,

Nicholas, Tamsen and Jonathan.

Bless you for your support.

It's in everyone of us to be wise

Find your heart, open up both your eyes

We can all know everything without ever knowing why

It's in everyone of us by and by...

John Denver.
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**FIELDS OF STUDY**

Major Field: Agricultural Engineering

Studies in Decision analysis, knowledge bases, modeling.
# TABLE OF CONTENTS

- DEDICATION .......................................................................................................................... ii
- ACKNOWLEDGEMENTS ........................................................................................................ iii
- VITA .......................................................................................................................................... iv
- PUBLICATIONS ....................................................................................................................... v
- FIELDS OF STUDY ................................................................................................................... ix
- TABLE OF CONTENTS ............................................................................................................. x
- LIST OF FIGURES ..................................................................................................................... xiv
- LIST OF TABLES ....................................................................................................................... xvii
- LIST OF PLATES ...................................................................................................................... xviii
- LIST OF SYMBOLS .................................................................................................................... xix

# CHAPTER I ................................................................................................................................. 1

  BACKGROUND .......................................................................................................................... 1
  Introduction ................................................................................................................................ 1
  Decision analysis ......................................................................................................................... 2
  The application ............................................................................................................................ 3
An application ................................................................. 73
Hardware ..................................................................... 77
Software ..................................................................... 77
Concept testing ............................................................... 78
Communications ............................................................. 80
The greenhouse climate control computer .................. 81
The nutrient injector ....................................................... 81
The Irrigation distribution system .............................. 82
The Greenhouse .............................................................. 86

CHAPTER VI ..................................................................... 89

OPERATION OF THE MODEL ........................................... 89
Flow chart .................................................................... 89
Input/Output ................................................................ 92

CHAPTER VII .................................................................. 98

RESULTS AND CONCLUSIONS ....................................... 98
Results ........................................................................ 98
Conclusions ................................................................. 101
Recommendations and future research ....................... 102

LIST OF REFERENCES .......................................................... 104

APPENDIX A ................................................................. 114

REVIEW OF TECHNOLOGIES ............................................ 114
Introduction ................................................................. 114
Decision Making .......................................................... 115
Decision Analysis ......................................................... 116
Probability .................................................................... 117
Inference ....................................................................... 118
Development of expertise ........................................... 119
Artificial Intelligence ..................................................... 121
LIST OF FIGURES

Figure 2.1 Indifference between actual outcome and a probability, p, at the best outcome ................................................. 10

Figure 2.2 Estimate of the probability, p, of the best outcome, given the path, or cultural practice to that outcome .................. 11

Figure 3.1 Relationships within the model ........................................ 19

Figure 3.2 Creation of feasible decision options .................................. 23

Figure 3.3 Probability determination .................................................. 25

Figure 3.4 Derivation of the path evaluation function .......................... 28

Figure 4.1 Assembly of nutrient recipes .............................................. 44

Figure 4.2 Solar irradiance probability prediction .................................. 47

Figure 4.3 Chance node showing the radiation transmission factor and a corresponding probability distribution (parameters a=4.0, b=2.0) ......................................................... 49

Figure 4.4 Histogram of the solar radiation transmission factor against probability ......................................................... 50

Figure 4.5 PDF for $G (6.6771, 0.3901)$ ................................................. 58

Figure 4.6 CDF for $G (6.6771, 0.3901)$ .................................................. 59

Figure 4.7 PDF for $G (1.8053, 3.1855)$ ............................................... 61
Figure 4.8 CDF for $\beta (1.8053, 3.1855)$ .................................................. 61
Figure 4.9 PDF for $\beta (2.3351, 0.3858)$ .................................................. 63
Figure 4.10 CDF for $\beta (2.3351, 0.3858)$ .................................................. 64
Figure 4.11 PDF for $\beta (1.6282, 3.9147)$ .................................................. 66
Figure 4.12 CDF for $\beta (1.6282, 3.9147)$ .................................................. 66
Figure 4.13 Derivation of the utility function .............................................. 71
Figure 4.14 A schematic of the complete model showing the relationships between nodes .................................................. 72
Figure 5.1 Layout of the irrigation and nutrient feed decision model ............ 76
Figure 5.2 Schematic of the communication layout between the decision computer, the control computer and the nutrient injector .................................................. 87
Figure 5.3 Nutrient flows and control paths in the cucumber growth experiment .................................................. 88
Figure 6.1 Flow chart of the model ............................................................... 90
Figure B.1 Layout of the cucumbers in the greenhouse ................................ 127
Figure B.2 Graph showing the irrigation schedule followed in the greenhouse .................................................. 129
Figure B.3 Graph of Nitrogen concentrations during the growing period ........ 131
Figure B.4 Graph of Phosphorous concentrations during the growing period .... 132
Figure B.5 Graph of Potassium concentrations during the growing period ....... 132
Figure B.6  Graph of Calcium concentrations during the growing period.................................133
Figure B.7  Electrical conductivity of the nutrient solution.................................134
Figure B.8  Nitrogen concentrations of the nutrient solution.................................135
Figure B.9  Phosphorous concentrations of the nutrient solution.................................135
Figure B.10  Potassium concentrations of the nutrient solution.................................136
Figure B.11  Calcium concentrations of the nutrient solution.................................136
Figure B.12  Magnesium concentrations of the nutrient solution.................................137
Figure B.13  Electrical conductivity of the nutrient solution and the leachate.................................138
Figure B.14  pH values of the nutrient solution and the leachate.................................138
Figure E.1  Irradiance transmissions and reflections in the greenhouse and crop canopies.................................157
LIST OF TABLES

Table 4.1 Nutrient solutions used.................................................................39

Table 4.2 Fertilizer concentration limits for cucumber "Mustang" at various growth stages.........................................................40

Table 4.3 Ranges of nutrient concentrations in mg.l-1..................................42

Table 4.4 AM Weather details by date............................................................52

Table 4.5 Forecast against irradiance ratio....................................................54

Table 5.1a Solution concentrations from fertilizer amounts and purities.............................................................79

Table 5.1b Injector head settings giving the concentrations of individual nutrients........................................................................80

Table D.3 Ozone thickness, uo, in mm..............................................................146

Table D.4 Tr factor as a function of m.............................................................148

Table E.1 Statistics on actual vs. calculated values from Stanghellini......154

Table E.2 Parameter relationships to air temperature...................................160
LIST OF PLATES

Plate I  Computer controlled Anderson Ratio:Feeder®.................................84
Plate II  The irrigation supply system mainlines, laterals and emitters.......85
Plate III  Photograph of the layout in the greenhouse showing plants
           and irrigation scheme.................................................................128
### LIST OF SYMBOLS

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a )</td>
<td>( \beta ) distribution parameter</td>
</tr>
<tr>
<td>( a_{\text{uv}} )</td>
<td>ozone absorption of ultraviolet radiation</td>
</tr>
<tr>
<td>( a_{\text{vis}} )</td>
<td>ozone absorption of visible radiation</td>
</tr>
<tr>
<td>( a_{\text{o}} )</td>
<td>ozone absorption of ultraviolet radiation</td>
</tr>
<tr>
<td>( \omega_b )</td>
<td>the albedo of the atmosphere</td>
</tr>
<tr>
<td>( \omega_s )</td>
<td>the albedo of the earth’s surface</td>
</tr>
<tr>
<td>( a_{\text{w}} )</td>
<td>absorption due to water vapor in the atmosphere</td>
</tr>
<tr>
<td>( \beta(a,b) )</td>
<td>the beta distribution</td>
</tr>
<tr>
<td>( b )</td>
<td>( \beta ) distribution parameter</td>
</tr>
<tr>
<td>( B_a )</td>
<td>amount scattered downwards by aerosols</td>
</tr>
<tr>
<td>( c )</td>
<td>the mode of the ( \beta ) distribution</td>
</tr>
<tr>
<td>( C_p )</td>
<td>specific heat of dry air</td>
</tr>
<tr>
<td>( D )</td>
<td>solar diffuse irradiance received at the earth’s surface</td>
</tr>
<tr>
<td>( \bar{d} )</td>
<td>mean sun distance</td>
</tr>
<tr>
<td>( d )</td>
<td>actual sun distance</td>
</tr>
<tr>
<td>( \delta S )</td>
<td>slope of the saturation vapor pressure curve</td>
</tr>
<tr>
<td>( \delta )</td>
<td>solar declination</td>
</tr>
<tr>
<td>( D_{\text{A}} )</td>
<td>diffuse irradiance component from aerosols</td>
</tr>
<tr>
<td>( \Delta D )</td>
<td>difference in wet bulb depression between surface and upper level</td>
</tr>
<tr>
<td>( D_R )</td>
<td>diffuse irradiance component from Rayleigh scattering</td>
</tr>
<tr>
<td>( D_s )</td>
<td>diffuse irradiance component from backscatterance</td>
</tr>
<tr>
<td>( \varepsilon )</td>
<td>ratio of molecular weight of water vapor to dry air (0.6216)</td>
</tr>
<tr>
<td>( e_a )</td>
<td>prevailing vapor pressure of air (mb)</td>
</tr>
<tr>
<td>( E_0 )</td>
<td>potential evapotranspiration (mm.s(^{-1}))</td>
</tr>
<tr>
<td>( e_s )</td>
<td>saturation vapor pressure at air temperature (mb)</td>
</tr>
</tbody>
</table>
\( \phi \) latitude

\( G \) Heat flux into the soil (W.m\(^{-2}\))

\( \gamma \) psychrometric constant ( = 0.66 mb.K\(^{-1}\))

\( \Gamma(t) \) the gamma function

\( H \) hour angle which includes the ephemeris of the sun.

\( I_{\text{crop}} \) radiation absorbed by the crop

\( I_0 \) solar constant (1353 W.m\(^{-2}\))

\( K_{\text{EX}} \) extra-terrestrial solar irradiance

\( K_{\downarrow} \) total clear sky irradiance received at the earth's surface

\( \lambda \) latent heat of vaporization of water (J.Kg\(^{-1}\))

\( m \) relative optical air mass

\( \mu \) the mean of the \( \beta \) distribution

\( n \) number in the data sample

\( p_k(j) \) probability of the occurrence of the \( j^{th} \) irradiance range using the \( k^{th} \) \( \beta \) distribution specified by the forecast

\( p_a \) air pressure (mb)

\( p_0 \) atmospheric pressure at sea level (101325 Pa)

\( q \) humidity ratio

\( Q^{*} \) incoming energy

\( Q_E \) energy absorbed by evaporation

\( Q_g \) outgoing energy

\( \rho \) density of dry air (Kg.m\(^{-3}\))

\( r_a \) resistance to water vapor transport outside the evaporating crop surface (s.m\(^{-1}\))

\( R_n \) total solar irradiance at earth's surface (W.m\(^{-2}\))

\( S \) solar direct irradiance received at the earth's surface

\( \sigma \) the standard deviation of the \( \beta \) distribution

\( s \) the standard deviation of a data sample

\( t_a \) dry bulb temperature (°C)

\( T_{\text{a}} \) transmission after attenuation by aerosols

\( T_{F} \) transmission factor at the mode of the \( \beta \) distribution

\( T_{0} \) absolute temperature at 0°C (273 °K)

\( T_{0}^{\text{r}} \) radiation transmission after absorption by ozone

\( T_{R} \) transmission after Rayleigh scattering
tw  wet bulb temperature (°C).

\( u(i,j) \)  plant growth function for the \( i^{th} \) recipe of nutrients and the \( j^{th} \) irradiance range

\( u_0 \)  thickness of the ozone layer

\( u_w \)  precipitable water in the atmosphere

\( w_0 \)  total amount attenuated by aerosol

\( \bar{x} \)  mean of a data sample

\( x \)  data variable

\( y(i) \)  expected value of the \( i^{th} \) recipe or option

\( z \)  solar zenith angle
CHAPTER I

BACKGROUND

Introduction

In agriculture many management decisions are repetitive and made in the context of limited resources, with limited knowledge of possible future events. These decisions are important to the growth and nurturing of crops because actions taken early in the life of a plant can profoundly affect its health and total yield. Plant growth management expertise results from years of cultivating living plants, and decisions are influenced by experience garnered over the years.

There exists a need to be able to coordinate many inputs, both objective and subjective, in order to make decisions which satisfy minimum standards of all variables. The effects of some decisions may remain unknown for a long time and thus systems of control through feedback become impossible. Often the outcomes can only be estimated, but there exists the ability to make reasonable predictions based upon the expertise of people knowledgeable in the area. Computerized decision making seeks to benefit from this human expertise.

Horticultural production, a prime example of controlled environment agriculture, could usefully incorporate the concepts and practicalities of computerized decision making. Consideration of all of the management options required to be evaluated in a horticultural operation is
an enormous task. According to Sullivan, Wilcox and Ooms (1988),
competition in the production of horticultural crops continues to intensify.
They examined planting, variety selection, fertilization, pest management,
disease and weed control and harvest and delivery. They proposed the
adoption of the more advanced techniques of artificial intelligence and
expert systems as possible solutions.

**Decision analysis**

The science of decision analysis has been assembled over many years
to analyze various outcomes of decision options in order to conclude which
option would be the most advantageous (Anderson 1977, Bell 1977, Hillier
von Winterfeldt 1986). The construction of decision trees and the use of
probabilities and utility functions to arrive at an optimal decision out of a
set of options has been used for scenarios from investments to fire fighting
to the siting of the Mexico airport (Hax 1977, Cohan 1984, Keeney 1976, de
Neufville 1986). The methodology has been established and the Bayesian
view of probability is straightforward and mathematically sound
(Cheeseman 1984, Berger and Berry, 1988).

Decision analysis necessitates the derivation of the probabilities,
outcomes and/or utilities that are required to construct a decision tree. The
computer science world, in its research into artificial intelligence, has
introduced a computer programming approach commonly referred to as an
inference engine which could be used to give probabilities, outcomes, and
utilities. An inference engine is an algorithm used with knowledge bases to
infer, conclusions. Such a system comprising an engine and knowledge base is called an expert system, as the knowledge based files are usually constructed from the knowledge of a person or persons having expertise in the area of concern.

In analyzing the respective roles played by experts and decision analysts, it was concluded that the expertise gained through years of experience by an expert could be referred to as "soft logic" (Roller 1987/88). It is not founded in math, it could be perfectly sound, and it would be subject to manipulation by changes of evidence.

Conversely, the science of decision analysis could be referred to as "hard logic." Decision analysis was founded in math with very specific theorems and proofs. Varying inputs could produce varying outputs, but the means by which those outputs were computed remained the same.

The purpose of this study was to examine whether decision analysis, with its mathematics or "hard logic" approach, and expert systems, with their intuitive expertise or "soft logic", could be combined in a model in such a way that the model could make consistent, repetitive, short-term decisions. If this proved to be so, then could that model be assembled in such a way that a computer could make such a "decision" and act upon it?

The application

If such a model could be built and implemented within a greenhouse, then its use could move the grower from being a person who makes operational decisions to one who makes tactical decisions.
Operational decisions made on the production of a vegetable crop grown in an Ohio greenhouse during the winter months incorporate considerations of incoming solar radiation, heating and ventilating, carbon dioxide enrichment, irrigation and nutrient supply and the possibility of disease and/or pests. The production of the vegetable depends on maintaining the growth parameters, temperature, relative humidity, carbon dioxide concentration, radiation, and water and nutrient supply, within predefined limits to achieve acceptable growth, fruit output and quality. These limits vary depending upon the maturity of the plant, the type of vegetable that is being grown, the environmental conditions and the solar radiation available.

Some of the parameters change value quickly and some change slowly. Temperature and relative humidity effects of heating and cooling the air could be evident within seconds, particularly close to heating pipes. Plant uptake of water and nutrients have time constants of the order of minutes. Intermittent solar energy fluctuations can have time constants of minutes, but major radiation fluctuations take place diurnally. Finally, the item which is the most important, the fruit, takes weeks or months to reach maturity and then fluctuates in production from one day to the next.

Identification of the controllable variables, the stochastic variables and the indices of performance would be crucial to the successful operation of the model.
Objective

The objective of the research was to construct a decision making model that would exploit the advantages of both decision analysis and expert systems in such a way that the model would make better decisions than those made by either concept used alone. The model would be applied to a specific problem of nutrient feeding in horticulture.

Model requirements

The proposal was to formulate a decision model for use in controlled environment agriculture that would apply to classes of problems that had the following characteristics:

1 requirement of real-time control;
2 identifiable actions that could be taken;
3 dependence upon future occurrences which were probabilistic in nature;
4 outcomes whose values were based upon non-monetized as well as monetized entities, and;
5 ability to enhance results by adaption and learning.

The model would conclude which option out of those available to the operator was the most advantageous from the point of view of the environment, the crop and the responsible use of resources. The model's strength lay with decisions that were made on a repetitive, short term, basis.
CHAPTER II

DECISION TREE EVALUATION

Introduction

Implicit in the construction of the decision tree was an estimate or statement of the outcome associated with each path in the tree. If the decision maker was a person who believed in the expected monetary value concept, that outcome would be the outcome associated with a particular path. For example, an investment of a sum of money at a particular interest rate dictated the total value of the sum of money after a given time period. The only unknown was the probability of occurrence of that particular interest rate. Examples in texts such as Raiffa on decision analysis, of picking a colored ball from a bag containing a mixture of balls, had outcomes defined by the color of the ball picked. The probability of picking a particular color did not effect the outcome. In this manner, the path dictated the outcome. The decision maker could modify the approach to this value by the use of the utility function which considered the decision maker's attitude towards money or value and modified the outcome appropriately.

In the evaluation of the decision tree in the model a value had to be placed at the tip of each branch of the tree. The difficulty was that the tree was concerned with a small period in time during which nothing easily measurable happened to the crop in the nutritional sense. What was the outcome of feeding the crop with a specified recipe of nutrients in a particular environment under a particular solar irradiance? How could a
decision tree be evaluated if there was no outcome in the conventional sense specified at the tips of the branches?

The model discussed in this dissertation operated on the basis that the outcome was defined by the path to the tips of the tree. The questions were: "How should that path be evaluated, and, could that evaluation be regarded as an index of performance of the system?"

An existing control system, adaptive control, which has been thoroughly investigated by others (Doeberlin, Ogata) was studied to ascertain whether or not its concepts could be used to facilitate this outcome evaluation.

**Performance indices**

The basis of adaptive control rested in the premise that there was some condition of operation or performance for a system which was better than any other. Such performance was defined in terms of the performance index. Characteristics considered desirable for the performance index were reliability, selectivity and applicability (Ogata).

The performance index gave the upper limit of performance of the system. Therefore, selection of the proper performance index was most important in the model.
The following functions had to be considered:

1. Identification of the dynamic characteristics of the system,
2. Decision making based on the identification of the system, and,
3. Modification or instruction based on the decision made.

If the system was imperfectly known, then the initial identification, decision and modification procedures would not be sufficient to maximize the performance index. In the adaptive control system, it became necessary to carry out these procedures continuously or at intervals of time, depending on how fast the system parameters were changing. This constant self-evaluation to compensate for unpredictable changes in the system was the aspect of performance which was usually considered in defining an adaptive control strategy.

Unfortunately, botanical plants are imperfectly known. Further, the plant parameters could not all be monitored and so these procedures were not sufficient to maximize the performance index of a botanical plant. Measurable system parameters changed much more slowly than the requirement for nutrition by the plant, making the adaptive control route an unusable option. The next question was: "Should the index have been changed to something that was measurable in the short term, or could the index have been estimated in some other fashion?"

Items that were measurable in the short term included photosynthetic rate, movement of chemical elements, and cell wall
thickening amongst others. All of these items were expensive to measure and could not be done on a continuous basis on many plants on a large scale in a commercial greenhouse. This led to the evaluation of the outcomes of the decision tree in another fashion. One difficulty of evaluating the paths in the tree was that different outcomes could be used as indices of performance of the production system depending upon what the grower was trying to achieve. The most obvious index of performance was that of the value of crop output. It was the sale of produce that kept the grower and family in business. However, this had to be tempered by the quality/quantity problem, by resources available to the grower, and responsibility to the environment and others living in the neighborhood.

Utility

The concept of the utility function in decision analysis as a means of placing values on outcomes seemed to be one that could be exploited. Normally the utility function was an indifference function which related the subject's indifference between having a particular outcome for certain and a chance, p, at the best outcome. That path was then allocated the "value" p. Note that the utility was based upon the decision maker's indifference to an outcome that was already established.

The question to the expert in a normal utility scenario should be: "What probability of achieving the best result is equivalent in utility to the outcomes that will result from this path?" Figure 2.1 illustrates the problem. The tilde, \( \sim \), indicates indifference.
This was impossible to answer, because the expert could not determine with certainty (a probability of 1.0) the actual outcome of the path. Referring back to the discussion of the textbook decision tree above, the ratios of the number of colored balls in the bag was not known, nor could a sample be taken to determine possible ratios. However, the expert definitely had an opinion built from years of experience about the probable outcomes of particular paths in the tree. For this reason the concept of a modified, or pseudo-utility function was selected for use.

The question to the expert now became: "What is the probability of achieving the best crop, given the path taken to this outcome?" If a high nitrogen, high potassium and low calcium recipe was fed to a fruiting crop on a day with low light levels (a particular path through the tree), how would the expert evaluate that path? It was not so much a matter of indifference between a definite outcome and the probability of the best outcome, as the grower's estimate of the best outcome being the result of
this particular cultural practice. Figure 2.2, when compared with Figure 2.1 illustrates the difference between the two concepts.

![Diagram of Cultural Practice]

Figure 2.2 Estimate of the probability, $p$, of the best outcome, given the path, or cultural practice to that outcome.

For this reason the function was described as a pseudo-utility function as it was not strictly a pure utility function.

Substitutability

The assumption of substitutability in utility dictates that when a particular outcome is defined at the tip of a decision tree, then that outcome can be substituted by the decision maker's utility of that outcome. Did the fact that there was no defined outcome at the tips of the decision tree violate this principle of utility? It is proposed that this was not the case because of the following argument:
1. Outcomes of a classical decision tree are defined by the path to that outcome, and

2. the utility of that outcome is defined by the decision maker's attitude towards that outcome.

3. Thus the utility is defined by the decision maker's attitude towards the path resulting in that outcome.

4. The model evaluated the utility of an outcome by the path taken to derive that outcome. The outcome itself did not need to be known.

Transitivity

The assumption of transitivity in utility dictates that if outcome 1 is preferred to 2, and outcome 2 is preferred to 3, then outcome 1 is preferred to 3. The model obeyed this dictate because of the fact that utilities were derived from the paths in the tree. If path A was better than path B, and path B was better than path C, then path A was automatically better than path C because it would have been allocated a larger pseudo-utility.

It can be seen that the function met the requirements of the utility function used in decision analysis with the exception of the indifference concept. Future research on the decision model using mathematical, rather than intuitive, simulation for prediction of the outcomes, will permit the use of a pure utility at this point in the tree. The operator will then be able to evaluate how he or she feels about the value of the outcome and will be
able to specify a real utility function at the tips of the tree branches without invalidating the concept of the model.

**Function name**

This pseudo-utility function was called a *crop response function* because it was the evaluation of the response of the crop in terms of quality and yield under the circumstances defined by the path in the tree.
CHAPTER III

SYNTHESIS

Introduction

The fundamental process that was being modeled in this work was one of competent decision making. It was not a model that made expert decisions, but one that drew upon a large base of experience to make competent decisions. It was established upon known principles, facts and accepted knowledge. Relevant scientific disciplines involved were those of decision making, stochastic processes, utility functions, plant science, climatology, computer modeling, electronics and control. Some may regard the processes as intelligent, but the interpretation of the Dreyfus brothers was preferred; that is, the processes were competent at best, and were probably moving from the novice stage to the competent stage.

Model selection

The decision model attempted to mimic the human in the logical sequence of making a decision. There seemed to be at least two very different modes of decision making with a continuum of decision types between them. There was the classical, complex decision which involved long projections into the future with an elaborate decision tree being constructed of many decision nodes with a chance node between each decision. Utility functions may or may not have been used in the tree and the tree itself was usually based upon economic criteria. There was often
much effort dedicated to the construction of the tree as the evaluation of the
tree was usually a simple mathematical process. The "rightness" of the
decision was directly related to the accuracy of the tree model which, in its
turn, was reflected in the research that constructed the tree.

Then there was another type of decision which occurred almost
continuously. This type of decision was characterized by the fact that it was a
short-term decision about a relatively narrow range of options, containing
both subjective and objective inputs. This decision was usually made
rapidly with an outcome derived from experience and, once acted upon;
may have been continually re-evaluated. Often, when faced with the
question, "Why did you do that", the decision maker found it difficult to
explain his or her actions. An example could be found in the decisions
made while driving a car to work along a familiar road:

In analyzing the ways in which humans make decisions it was
acknowledged that decisions of the second type were made on the basis of a
wealth of knowledge and prior experience. Consultation with an expert was
only conducted when and as necessary. This may have been due to expense
or availability, or simply that the decision-maker thought that he or she
knew better anyway. However, it seemed that the way in which most
repetitive decision-making was done was to follow, albeit unconsciously,
the building of a decision tree; that is:

1 assemble all of the available options open to the decision-
maker under the circumstances and at this moment in time;
2 detail the unknowns that may occur after the point in time that the decision is taken and before the next decision will have to be made;

3 allocate the probabilities of occurrence to the unknowns using statistical evidence or heuristics;

4 compute the outcomes using a model to evaluate all paths in the tree; and,

5 fold back the assembled decision tree to find out which decision to make.

6 (1) assemble new options.

This was much like a complete decision tree analysis, except that it was a circular tree in an infinite loop. This tree could be applied by a decision maker, but it would also work well in a computer application. Some areas would have to be enhanced by using knowledge bases as a subsidiary guide within the above structure.

Assembly of the model

Recall that the objective of the work was to combine the sciences of decision analysis with those of expertise to develop a decision making model that would be superior to decision analysis or expert systems employed alone.
The question was, "Could the use of expert systems from artificial intelligence be exploited within the science of decision analysis to:

specify outcomes from an evaluation of the path in the tree from the decision option to the outcome, and

specify probabilities of the chance nodes within the tree, and

act as "nonsense filters" in the selection of decision options that would be considered in the tree?"

The "nonsense filter" was defined as a concept which filtered out unnecessary items from consideration as early on in the process as possible (Corsberg 1987). This minimized computing time of the model.

The methods by which decision analysis and expertise might be beneficially combined was discussed with Dr. Roller, my advisor. Expert systems available at the time were usually used in such a way that they would consult knowledge bases to come to a conclusion (McKinion, Duda, Feigenbaum, Langlotz, and Shortliffe). If it was necessary, the expert system would use an external program to compute an answer to a problem and then return to consideration of the rulebase.

Dr. Roller made the suggestion that, rather than hang the "hard logic" of the decision tree or other mathematical models onto the "soft logic" of the rulebase, why not turn the concept inside out and use the "hard logic" of the decision tree as the foundation of the model, hanging the "soft logic" of the expert systems onto the tree to be consulted as necessity demanded?
This resulted in a re-evaluation of the concept which permitted the continual replacement of intuitive parts of the model with mathematical equations as research results became known (Roller 1987, 1988).

The result was the use of the decision tree as a foundation for the model with reference to various simulations, knowledge base consultations and mathematical computations as deemed necessary. A representation of the relationships between the systems is shown in Figure 3.1.
Figure 3.1. Relationships within the model
Construction of the model

The model was assembled in the computer as a number of program shells. There was an overall shell which was the Apple Macintosh shell which dealt with windowing and input and output. There was the decision analysis shell which consulted the expert system, ran simulations and averaged out and folded back the decision tree, sending its output to the Macintosh shell. Finally, there was the expert system shell which consulted rulebases when requested by the decision shell.

At the commencement of each decision period, feasible decision options were assembled from a rulebase on nutrients. Then probabilities for each event in the chance node were fed to the decision shell. The decision shell then charted a path incorporating a decision and a chance and consulted another rulebase about the outcome of that particular decision followed by that particular event.

This process continued until all decision options and all events in the chance node had been exhausted. When all outcomes had been derived, either by simulation or by inference, the cross-product of the probabilities and the outcomes was computed, giving an expected value for each option. The option with the maximum expected value was selected. The decision was implemented by sending a control signal to the relevant piece of equipment or machinery.
The Generic Decision Tree

The generic decision tree was constructed from a single decision node, followed by a single chance node, which was followed by a single path evaluation node which could be considered to be a utility node with some modifications in the final application. A discussion of each node in the generic tree follows.

The Decision node

Figure 3.2 shows how the decision options were assembled from the base of known facts by the knowledge base of items and legal values using the expert system shell in the model.

Examples of the crop type could be cucumber, or tomato, or roses, or lilies, but is not restricted to those. Each type could have a subtype, so cucumbers would include the variety Mustang and tomato would include the variety CR6 and so on. If it was known that a particular variety of tomato at a particular physiological age did well on a higher nitrogen than other types, then it made sense to note that in this node. That fact was not dependent on the items in the tree that followed this node. There was no point in considering low nitrogen, if, at that stage in that plant's growth cycle, low nitrogen would not be used. This was how the filtering of the information was done so that the feasible option list was no larger than that required to make a competent decision.

Each variable, or item, had a set of legal values, that is, values that would be acceptable. The expert system sorted these values depending upon
the known facts and established a set of options to be considered. The assembly of this node required care. All options that were relevant had to be considered, but one more option than necessary at this point in the tree increased the number of computations by the computer.
Known facts
These are known facts such as crop type, crop variety, physiological age, time of day.

Items + Legal Values
Item 1
Item 2
Item 3
Item 4
Item 5
Item ...
Item m-1
Item m

Main decision options assembled from pre-prioritized, pre-defined items using intelligent selection
Feasible Decision Options
Option 1
Option 2
Option 3
Option 4
Option ...
Option n

Figure 3.2. Creation of feasible decision options
The chance node

The same expert system shell was used to consult a probability knowledge base to derive the parameters for an appropriate probability density function. These probabilities were assigned to respective interval values or events by integration of the probability density function. This node is depicted in Figure 3.3.

Multiple chance nodes could be assembled in this manner, following on from the decision node. In agriculture this could be used to advantage because many decisions are followed by a number of environmental factors that the grower or farmer cannot control. As an example, the outcome of a spraying program in an orchard may depend upon solar radiation levels, wind velocity, temperature and location of the pest. Each of these would have their probability distributions, and some would depend upon others, but the decision would have to be made with the best understanding of each and all of the items.

Each chance node would be constructed of a continuum of probabilities to describe ranges of events of items such as the solar radiation, rainfall, wind speed, wind direction, temperature and relative humidity probabilities.

For the purpose of this dissertation a single chance node was used to model the probabilities for particular ranges of solar radiation transmission factors predicted from the weather forecast.
Facts

Predefined parameters such as:
- date and time
- weather forecasts
- distribution functions

Determination of the probability distribution of the chance node using an inference engine to obtain the function parameters

Integration of the distribution function over the intervals chosen

Interval values and their probabilities

Figure 3.3. Probability determination
The outcome

Each outcome in the decision tree was evaluated by assessing the path within the tree and specifying the probability of the "best possible result", given the path taken to that outcome. An example follows.

Given that:

1. the proposed nutrient recipe was x, and
2. the average solar irradiance for the forecast period was between 250 and 500 w.m\(^{-2}\),

then, "what probability of achieving an excellent result (and a complementary chance at the worst result) would be equivalent to the outcome that would result from this path?"

This was difficult to interpret and tended to be phrased:

"What would be the probability of achieving an excellent result if you continued to use the cultural practices evident in this path when the scenarios were such as those in the path?"

This path evaluation was derived from the experience of one person, a plant scientist, knowledgeable in the domain of the growth of the plant. It was the result of an intuitive simulation of each path of the decision tree, as mathematical simulation of plant growth was not available. The value for "u" shown in Figure 3.4 was derived from the knowledge base built from the expertise of the plant scientist.
This function could be very complex. If more than one chance node was used in the tree, the outcome had to consider all of them at the same time, and, in the event that the outcome was multi-attributed, consideration had to be given to the independence of each attribute. The model developed had only one chance node, but path evaluation was made on the basis of yield and quality. These two attributes were considered by the expert as inseparable and were evaluated together.
Knowledge Base

rule 1
rule 2
rule 3
... rule k-1
rule k

Outcomes derived from a rule-based system which has been learned from an expert in the field

Outcomes placed in the decision tree complex

u
Best possible result

Outcome node

1-u
Worst possible result

Figure 3.4. Derivation of the path evaluation function.
The final decision model

The final decision model comprised of decision analysis and expert system techniques met the requirements of the classes of problems delineated in Chapter I as follows:

1. requirement of real-time control.

This was implemented on a dedicated computer in the concept of the loop together with predictions of the environmental conditions that would be prevalent in the next few hours.

2. identifiable actions that could be taken.

The assembly of the decision options was done by an expert system that took into account the resources available and decided which to use based upon data such as plant maturity prevailing at the time.

3. dependence upon future occurrences which were probabilistic in nature.

The decision depended upon upcoming criteria which were reflected in the chance node of the decision tree.

4. outcomes whose values were based upon non-monetized as well as monetized entities.
This point was enabled by the use of simulation models when available, and by the use of plant growth expert systems and utilities when simulation models were not available.

Quality of product, path entropy, environmental impacts, cash flow and other relevant judgements should all be able to be incorporated into the decision making process. The use of expertise and utility functions allowed the estimation of outcomes that were not directly quantifiable.

5  ability to enhance the results by adaption and learning.

The use of a procedure to compare the actual historic data from day to day with the forecast data for that day allowed the updating of the probability function for use with future estimates. This enabled the system to adapt to the environment in which it was working. Learning would be accomplished by the simple changing of rules in the rule-base that the model uses. These rule changes would reflect new knowledge being gained by researchers in the area of application.
CHAPTER IV

DERIVATION OF SYSTEM PARAMETERS

Introduction

The art of decision making lies in being able to make "good" decisions within the realms of risk and uncertainty. Unfortunately most decision makers are not able to have all the facts at their fingertips when the time comes for a decision to be made and the grower is no exception. The problem of weather forecasting was a case in point. The grower and decision model had to be able to cope with these uncertainties.

In discussions with Dr. William Bauerle of the Horticulture Department of the Ohio Agricultural Research and Development Center (OARDC), The Ohio State University, it was established that a nutrient decision model would aid the grower in the management of cucumbers, tomatoes, bedding plants and ornamental crops in greenhouses. Timely supply of nutrients to the individual plant so as to make optimum use of available sunlight within the temperature and humidity constraints imposed upon the plant by the environment was essential. If the stress on the plant could be controlled by appropriate nutrient selection methods, then the plant would produce a higher yield of fruit or flower at a higher quality.

Dr. Bauerle had initiated the development of an individual element/nutrient injector for irrigation systems in controlled environment
agriculture. This introduced new decision opportunities where none had existed before. The use of a decision model in conjunction with this equipment would be essential to obtain the optimum performance from the new technology (Fraser 1986).

The grower could control temperature, humidity and nutrient supply, but not sunlight. The computer model optimized the nutrient supply according to the conditions that prevailed at the time and the probabilities applying to the forecast of sunlight conditions to come in the next few hours.

The use of the model would move the grower from being a person who made operational decisions to one who made tactical decisions. The greenhouse system as a whole would be monitored and controlled, and decisions would be made in real time by the computer, based upon probabilities of future events.

**Rulebase derivation**

There were four rulebases developed for incorporation into this decision model. They were as follows:

1. advises on the options open for the nutrient feeding program, the decision node,

2. proposes solar irradiance probability functions, the chance node,

3. provision of the utilities, the outcome, and
4. diagnosis of nutrient problems in the cucumber so as to react to possible deficiencies.

**Nutrient option rulebase**

The nutrient option rulebase related available nutrients to the crop type and maturity and to the environmental conditions prevailing at the time of the decision.

**Irradiance probability rulebase**

The clear sky irradiance figure for the day was calculated. The probabilities of the fraction of that radiation transmitted through the atmosphere were derived from the microclimate rulebase in conjunction with the weather forecast broadcast by AM Weather on the Public Broadcasting System. These were combined to give irradiance probabilities for the coming hours.

**Plant response rulebase**

This rulebase was derived by growing a crop and consulting with the horticulturist about the strategies to be followed for particular conditions. As both potential yield and quality of the crop were taken into account by the horticulturist, the evaluation of the path in the decision tree was, in effect, a multi-attribute function, modified to evaluate the path in the decision tree which resulted in that outcome.
Diagnostic rulebase

This rulebase was derived from the literature on cucumber nutrient deficiencies and toxicities, and from the growing of a cucumber crop in a greenhouse under the direction of a cucumber horticulturist.

Growing a cucumber crop

Background

Vegetables require water and nutrients at different rates and in different proportions according to temperature, relative humidity, available irradiance and plant maturity and condition. The decision options in the model were comprised of a mixture or recipe of nutrients. The unknown chance node was constructed from a probability distribution of future solar irradiance, and the tree paths were evaluated by a plant growth evaluation. This utility function was derived from discussions and interactions with an experienced cucumber horticulturist whilst growing a cucumber crop in the greenhouse#8, compartment#11 in the horticulture greenhouse complex at the Ohio Agricultural Research and Development Center in Wooster, Ohio.

From novice to competence

The discussion of the steps from novice to expert (Dreyfus 1986) covered a major point; that of creativity; or innovative solutions to problems. The expert person has an ability to perform in a way that produces remarkable, apparently intuitive, results. The advice from an expert comes from many years of learning and the ability to recall situations.
This made it difficult to ascertain how an expert derived a solution, because often the expert did not fully appreciate all of the inputs considered in order to come to a solution to a problem.

The interview technique of extracting information from the expert for this study did not seem to be a very efficient method from the point of view of time and it was clear that large chunks of information would probably be missed by the interviewer. It was decided to try an alternative method of information extraction.

Information extraction

As a result of the points mentioned above it was decided that one way to extract the relevant expertise from the expert would be for a novice to try and grow a cucumber crop while being aided by an horticultural expert. It was anticipated that this method would build a certain amount of competence in the novice and that a knowledge base could be assembled that would be used to evaluate the paths in the decision tree.

The greenhouse was declared off limits to the expert. He was not allowed into the greenhouse and the plants were screened off from the entrance so that he could not see them by inadvertently glancing through the glass in the doors. The greenhouse was a gutter connected house covered with double polyethylene plastic on the walls and roof, so that detailed observation of the crop from outside the greenhouse was not possible.
The novice and the expert were free to communicate in any way that they felt would impart knowledge to the novice. Four basic methods were used:

1. Communication by telephone. A telephone was installed in the greenhouse so that the novice could examine parts of the plants while communicating with the expert. This method forced the expert to use the novice as his eyes, nose, and fingers and required that the expert think carefully about the questions posed to the novice. These telephone conversations were recorded on tape so that they could be analyzed for advice later.

2. Direct communication. The novice and the expert held frequent discussions outside the greenhouse during which the novice attempted to understand some of the reasoning used by the expert. This reasoning was used in the novice's evaluation of the crop conditions and possible reactions to nutrient solutions under different ambient conditions.

3. Interpretation of leaf analyses. Leaf analyses were taken of the plants twice a week (Tuesdays and Fridays) during the growing and evaluation period. These analyses were examined by the expert and he made recommendations about appropriate changes in the nutrition program.

4. Direct observation. On three occasions during the growth of the crop, leaves were cut from a number of plants and taken
out of the greenhouse to the expert. He observed these leaves and the novice and the expert discussed possible problems with the crop and strategies to overcome those problems.

A videotape was made of the expert's reaction to the whole crop after six weeks in the greenhouse. This was instructive as the expert could see how recommendations had turned out in practice and he could react to the situation. This recording was studied to obtain an understanding of some of the problems that had developed during the growing period.

During this time the crop had to be maintained as free of pests and diseases as possible. The plants had to be trained up their supports, early fruit had to be taken off the plant to promote leaf growth, suckers had to be removed from the plants as they grew, fruit had to be picked, and samples had to be taken of the leaves and nutrient solution. The solution sampling and measuring of pH and electric conductivity of the solution was done by the novice. A technician skilled in the art of taking leaf samples performed that work. The injector system was in the prototype stage at this point in time and so any problems occurring with the system had to be rectified by the novice. Meanwhile the development and possible use of the model had to be coordinated, the telephone conversations analyzed, the tutorials understood and the interpretations digested!
Construction of the decision node rulebase

The first task was to assemble the decision options within the model. This required a knowledge base of the nutrient management and operational procedures. This knowledge base was built into the database of the model. The date, crop type and maturity of the crop dictated what kinds of nutrient decisions would be faced by the decision maker at any particular time. In an ongoing situation, historical data of the operation would have been stored and this data could be accessed to modify future decision options.

The initial selection of nutrients was dictated by the nutrients available to the grower. The Anderson injector could inject up to a total of ten nutrient mixtures, with eight of those being controlled from a remote station. The selection of the nutrients to be used at each injector station depended upon the different crops to be irrigated by the same machine. For this experiment one crop was used, so the selection was dictated by the fact that the crop was cucumbers. Many different formulations of nutrients were available and the decision was made to use those shown in Table 4.1.
Table 4.1 Nutrient solutions used

<table>
<thead>
<tr>
<th>Nutrient</th>
<th>Head #</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phosphoric acid</td>
<td>1</td>
</tr>
<tr>
<td>Nitric acid</td>
<td>2</td>
</tr>
<tr>
<td>Potassium Sulfate</td>
<td>3</td>
</tr>
<tr>
<td>Magnesium Sulfate</td>
<td>4</td>
</tr>
<tr>
<td>Mono Am Phosphate</td>
<td>5</td>
</tr>
<tr>
<td>Calcium Nitrate</td>
<td>6</td>
</tr>
<tr>
<td>Potassium Nitrate</td>
<td>7 &amp; 9</td>
</tr>
<tr>
<td>Urea</td>
<td>8</td>
</tr>
<tr>
<td>Micro-nutrients</td>
<td>10</td>
</tr>
</tbody>
</table>

Within the confines of the mathematical combinations of the mixtures allowed by these nutrients and their concentrations, the following basic rules were applied to select recipes. Recall that at this stage of the model operation, the solar irradiance figures were not known. The known items were:

- the crop type and variety,
- crop maturity,
- time and temperature,
- relative humidity,
- acceptable pH range,
- electrical conductivity limits, and
• the nutrients available.

Taking these items into account, Table 4.2 was compiled to aid in the selection of the nutrient recipes.

Table 4.2 Fertilizer concentration limits for cucumber "Mustang" at various growth stages.

<table>
<thead>
<tr>
<th>Growth stage</th>
<th>Electro. cond.</th>
<th>N as NO₃</th>
<th>N as NH₄</th>
<th>P</th>
<th>K</th>
<th>Ca</th>
<th>Mg</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plant-Flower</td>
<td>max</td>
<td>1800</td>
<td>200</td>
<td>0</td>
<td>75</td>
<td>400</td>
<td>200</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>min</td>
<td>1200</td>
<td>75</td>
<td>0</td>
<td>40</td>
<td>150</td>
<td>80</td>
<td>30</td>
</tr>
<tr>
<td>Flower-Fruit</td>
<td>max</td>
<td>2500</td>
<td>300</td>
<td>60</td>
<td>75</td>
<td>600</td>
<td>300</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>min</td>
<td>1400</td>
<td>150</td>
<td>5</td>
<td>40</td>
<td>300</td>
<td>60</td>
<td>30</td>
</tr>
<tr>
<td>Fruit onwards</td>
<td>max</td>
<td>2500</td>
<td>200</td>
<td>60</td>
<td>75</td>
<td>400</td>
<td>300</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>min</td>
<td>1200</td>
<td>50</td>
<td>5</td>
<td>40</td>
<td>100</td>
<td>80</td>
<td>30</td>
</tr>
</tbody>
</table>

Each element was maintained between the limits shown in the table. In addition, in order to keep the construction of recipes and their number to manageable proportions, the limits were split into low, medium and high.

The acids were used primarily for maintaining the pH at 5.4±0.2. Thus they effectively became a part of the background supply. pH is extremely difficult to compute, so changes in pH with changes in the acid
head settings were not computed, but measured, and the pH adjusted accordingly. In the future, it would be a good concept to control the acid supply directly with the pH meter. The computer could always read the head setting and take it into account when computing the concentrations of the nutrients in the supply water. An alkalinity curve should be plotted of the supply water before beginning the growth of the crop so that intelligent estimates of the acid required could be made. It was not done for this experiment.

The remaining compounds were used for control of nitrogen, phosphorus, potassium, calcium, magnesium and sulphur. Each item was split into different concentration levels according to the stage of the crop as shown in Table 4.3.
Table 4.3 Ranges of nutrient concentrations in mg.l⁻¹.

<table>
<thead>
<tr>
<th>Nutrient</th>
<th>plant-flower</th>
<th>flower-fruit</th>
<th>fruit onwards</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nitrogen</td>
<td>low</td>
<td>medium</td>
<td>high</td>
</tr>
<tr>
<td></td>
<td>75-120</td>
<td>120-160</td>
<td>160-200</td>
</tr>
<tr>
<td></td>
<td>150-200</td>
<td>200-250</td>
<td>250-300</td>
</tr>
<tr>
<td></td>
<td>50-100</td>
<td>100-150</td>
<td>150-200</td>
</tr>
<tr>
<td>Potassium</td>
<td>plant-flower</td>
<td>flower-fruit</td>
<td>fruit onwards</td>
</tr>
<tr>
<td></td>
<td>150-240</td>
<td>240-320</td>
<td>320-400</td>
</tr>
<tr>
<td></td>
<td>300-400</td>
<td>400-500</td>
<td>500-600</td>
</tr>
<tr>
<td>Calcium</td>
<td>plant-flower</td>
<td>flower-fruit</td>
<td>fruit onwards</td>
</tr>
<tr>
<td></td>
<td>80-120</td>
<td>120-160</td>
<td>160-200</td>
</tr>
<tr>
<td></td>
<td>60-140</td>
<td>140-220</td>
<td>220-300</td>
</tr>
<tr>
<td></td>
<td>80-150</td>
<td>150-230</td>
<td>230-300</td>
</tr>
<tr>
<td>Phosphorus</td>
<td>maintained</td>
<td>maintained</td>
<td>maintained</td>
</tr>
<tr>
<td></td>
<td>between 40 to 75 mg.l⁻¹.</td>
<td>between 30 to 50 mg.l⁻¹.</td>
<td>between 30 to 40 mg.l⁻¹.</td>
</tr>
<tr>
<td>Magnesium</td>
<td>maintained</td>
<td>maintained</td>
<td>maintained</td>
</tr>
<tr>
<td></td>
<td>between 30 to 50 mg.l⁻¹.</td>
<td>between 30 to 40 mg.l⁻¹.</td>
<td>between 30 to 40 mg.l⁻¹.</td>
</tr>
<tr>
<td>Sulphur</td>
<td>maintained</td>
<td>maintained</td>
<td>maintained</td>
</tr>
<tr>
<td></td>
<td>between 30 to 40 mg.l⁻¹.</td>
<td>between 30 to 40 mg.l⁻¹.</td>
<td>between 30 to 40 mg.l⁻¹.</td>
</tr>
</tbody>
</table>

After filtering the input information in the manner described above, the possible recipes available to the grower were combinations of the following:

3 levels of nitrogen, + 3 levels of potassium, + 3 levels of calcium, + 1 level of each of phosphorus, magnesium and sulphur, which totalled 27 recipes. However, a further filtering was possible. Potassium and nitrogen could be tied together if the nutrient ratios were correct. Maintaining a ratio of K/N at a minimum of 2 was deemed reasonable nutritional practice.
This was taken into account in the formulation of Table 4.3. This gave a total of 9 recipes as nitrogen and potassium could be tied together.

The decision tree objective was to search for the recipe with the maximum expected value as explained later in this chapter.

Figure 4.1 depicts the building of the decision options from the pre-defined conditions described above.
**Known facts**

- **Items + Range of values**
  - Crop type
  - Crop variety
  - Physiological age
  - Time of day
  - Temperature
  - Relative humidity
  - pH range
  - EC range

**Main decision nutrient recipes assembled from pre-prioritized, pre-defined nutrient concentrations and value ranges using intelligent selection guided by the known facts**

**Feasible Nutrient Recipes**

- Recipe 1
- Recipe 2
- Recipe 3
- Recipe 4
- Recipe 5
- Recipe 6
- Recipe 7
- Recipe 8
- Recipe 9

**Figure 4.1. Assembly of nutrient recipes**
Construction of the chance node rulebase

The model derived probabilities for solar irradiance transmission through the atmosphere from the weather forecast. These data were assembled from a history of weather forecasts and the ratio between solar irradiance received and the computed clear sky irradiance for particular days.

The chance node was a probability description of solar irradiance levels during the coming day. It was updated during the day by consideration of the immediate history of solar irradiance and comparing it to the probabilities derived at the beginning of the day.

Weather forecast data were input from "AM Weather", a television program broadcast each weekday morning on Public Television Service for airplane pilots. This program was being used at the time by some growers for decision making.

Letting \( j \) designate the number of irradiance ranges, and \( k \) designate the number of probability distributions of irradiance, then the probability of occurrence of the irradiance ranges, \( p_k(j) \), were computed from the clear sky irradiance, \( K_\downarrow \), and the probability density function, \( \beta \), as follows:

\[
p_k(j) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \int_{x(0,1)}^{\alpha(a+b)} x_{(a-1)}(1-x)(b-1) dx, \quad \{x \in (0,1)\} \quad (4.2)
\]

with: \( a \) and \( b \) being \( \beta \) parameters derived from the weather forecast.
\( \Gamma \) the gamma function, and

\[
\text{val}(1) = 0.0, \quad (4.3)
\]

\[
\text{val}(2) = \begin{cases} 
\frac{250}{K_{\downarrow}} & K_{\downarrow} > 250 \\
1.0 & K_{\downarrow} \leq 250
\end{cases}, \quad (4.4)
\]

\[
\text{val}(3) = \begin{cases} 
\frac{500}{K_{\downarrow}} & K_{\downarrow} > 500 \\
1.0 & K_{\downarrow} \leq 500
\end{cases}, \quad (4.5)
\]

\[
\text{val}(4) = 1.0 \quad (4.6)
\]

These relationships are described diagrammatically in Figure 4.2.

where \( R_{\text{n}} \) is the total irradiance at the earth's surface after accounting for all attenuation, i.e.:

\[
R_{\text{n}} = K_{\downarrow} \cdot \text{distribution fraction} \quad (4.7)
\]
Known facts

date  
time  
place (long., lat.)  
prediction "window"  
weather forecasts  
$\beta$ distribution function

Determination of the distribution function parameters of the solar radiation transmission factor, (0-1), from weather forecasts using an inference engine

Probability of occurrence of the solar irradiance intervals from integration of the $\beta$ probability density function

$P_k^{(1)}$ of $R_n > 500 \text{ w/m}$

$P_k^{(2)}$ of $500 > R_n > 250 \text{ w/m}$

$P_k^{(3)}$ of $R_n < 250 \text{ w/m}$

Figure 4.2. Solar irradiance probability prediction
Solar PDF and CDF

The $\beta$ probability density function (PDF) and the cumulative
distribution function (CDF) are described mathematically in Appendix C.

Figure 4.3 shows a possible distribution of irradiance transmission
factors corresponding to $a$ and $b$ parameters for the $\beta$ distribution of 4.0 and
2.0 respectively.

Figure 4.4 shows the same data in histogram form. Incorporation of
the value for the period involved of clear sky irradiance would give the
probabilities of the anticipated irradiance for that period.

In order to derive numbers for use in the model, two computations
had to be completed. The first was to find the clear sky irradiance figure for
the day in question, and the second was to compute the $\beta$ probability density
function for that day. Clear sky irradiance was computed as detailed in
Appendix D. The $\beta$ probability density function was derived from an
analysis of the weather forecasts and the clear sky irradiance values relevant
to each forecast.
Figure 4.3 Chance node showing the radiation transmission factor and a corresponding probability distribution ($\beta$ parameters $a=4.0$, $b=2.0$)
Figure 4.4 Histogram of the solar radiation transmission factor against probability.
Determination of the β distribution parameters

The β distribution parameters for solar irradiance transmission were derived from studying the weather forecasts of AM Weather during winter 1987 and comparing the forecast situations with the ratio of actual solar irradiance to the theoretical clear sky irradiance figure for that day. The factors recorded from the weather forecasts were:

1. the lay of any local weather front and its direction of movement,
2. the type of front; cold, warm or occluded,
3. which pressure system was nearest Ohio in meteorological terms, and
4. whether the forecast specified a clear space, a lightly overcast (light green) color, or a heavy overcast (dark green) color, upon Ohio.

The data gathered are shown in Table 4.4 arranged by date, and Table 4.5 arranged in order of the solar irradiance ratio. The position of the pressure system and the overlays in the forecast seemed to describe the clarity of the sky fairly well. Note that the overall distribution was bimodal (cf. Mustacchi, Cena and Rocchi 1979), as there were more occurrences of the fractions at the lower and upper ends of the scale than there were in the middle of the scale.
Table 4.4 AM Weather details by date

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<th>Clarity</th>
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Table 4.4 continued

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Table 4.5 Forecast against irradiance ratio

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Table 4.5 continued

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Analysis of the data

It would be appropriate at this point to discuss why the irradiance ratio exceeded unity on some days. The model for predicting clear sky radiation was only accurate to ten percent, and the atmospheric pressure was not available for the model predictions every day. These two points account for the discrepancy in the actual figures.

The numbers used in the derivation of the \( \beta \) distribution parameters were all kept to unity or less. It was accepted that this introduced further error and that this area of the model needs further investigation and analysis of more data in the future. Data were only available for the winter of 1987 when the experiment was run.

Derivation of the \( \beta \) distribution parameters

Recall the characteristics of the \( \beta \) distribution (Appendix C):

the mean,
\[
\mu = \frac{a}{a+b}\tag{4.8}
\]

and the variance,
\[
\sigma^2 = \frac{ab}{(a+b+1)(a+b)^2}\tag{4.9}
\]

where:

\( a \) and \( b \) are the \( \beta \) distribution parameters.
Taking the irradiance ratio figures from Table 4.5 that corresponded to "high pressure" and no fog gave the following sample statistics:

\[ \bar{x} = 0.9448 \] \hspace{1cm} (4.10)

\[ \Sigma x = 24.5650 \] \hspace{1cm} (4.11)

\[ \Sigma x^2 = 23.3708 \] \hspace{1cm} (4.12)

\[ n = 26 \] \hspace{1cm} (4.13)

\[ s^2 = \frac{n\Sigma x^2 - (\Sigma x)^2}{n(n-1)} = 0.00646 \] \hspace{1cm} (4.14)

Using the sample mean \( \bar{x} \) and sample variance \( s^2 \) as estimates of \( \mu \) and \( \sigma^2 \), the \( \beta \) parameters, \( a \) and \( b \) were derived as shown in Appendix C as follows:

parameter dum;

\[ dum = \frac{\bar{x}}{1- \bar{x}} = 17.1182 \] \hspace{1cm} (4.15)

Now, \( b \) was derived from

\[ b = \frac{dum}{s^2(dum + 1)^3} \cdot \frac{1}{dum + 1} = 0.3901 \] \hspace{1cm} (4.16)

and \( a \) from

\[ a = dum \cdot b = 6.6771 \] \hspace{1cm} (4.17)
Thus, if the AM Weather forecast showed Ohio in a high pressure, and the time of the year was winter and there was no fog shown, then the \( \beta \) distribution was described with the parameters \( a \) and \( b \) as shown in equations 4.16 and 4.17.

The probability density function, PDF, and the cumulative distribution function, CDF, for the values of \( a \) and \( b \) derived above are shown below in Figures 4.5 and 4.6

![Figure 4.5 PDF for \( \beta (6.6771, 0.3901) \)]
Similarly, taking the irradiance ratio figures from Table 4.5 that correspond to "low pressure" and fog or heavy overcast gave the following characteristics:

\[
\bar{x} = 0.3617 \quad \text{(4.18)}
\]

\[
\sum x = 5.0641 \quad \text{(4.19)}
\]

\[
\sum x^2 = 2.3328 \quad \text{(4.20)}
\]

\[
n = 14 \quad \text{(4.21)}
\]
a and b were derived as before:

\[ s^2 = \frac{n\Sigma x^2 - (\Sigma x)^2}{n(n-1)} = 0.03854 \] \hspace{1cm} (4.22)

Parameter \( \text{dum} \):

\[ \text{dum} = \frac{x}{1-x} = 0.5667 \] \hspace{1cm} (4.23)

\[ b = \frac{\text{dum}}{s^2(\text{dum} + 1)^3} \cdot \frac{1}{\text{dum} + 1} = 3.1855 \] \hspace{1cm} (4.24)

and

\[ a = \text{dum} \cdot b = 1.8053 \] \hspace{1cm} (4.25)

Thus, if the AM Weather forecast showed Ohio in a low pressure, and the time of the year was winter and there was fog or heavy overcast, then the function was described with the parameters a and b as shown in equations 4.24 and 4.25.

The probability density function, PDF, and the cumulative distribution function, CDF, for the values of a and b derived above are shown in Figures 4.7 and 4.8.
Figure 4.7 PDF for $\beta (1.8053, 3.1855)$

Figure 4.8 CDF for $\beta (1.8053, 3.1855)$
Adapting from one year to the next

During the experiment in the winter of 1988, these curves were updated with the weather forecasts and clear sky irradiance calculations at that time. This was an example of the capacity of the model to adapt to the conditions in which it was operating. The PDF and CDF curves derived from the $\beta$ distributions for high atmospheric pressure and clear days, and low atmospheric pressure and overcast days are shown below in Figures 4.9 to 4.12.

The statistics for the derivation of the curves for high pressure and clear days were:

\[
\bar{x} = 0.8582 \quad (4.26)
\]

\[
\Sigma x = 56.642 \quad (4.27)
\]

\[
\Sigma x^2 = 50.737 \quad (4.28)
\]

\[
n = 66 \quad (4.29)
\]

\[
s^2 = \frac{n\Sigma x^2 - (\Sigma x)^2}{n(n-1)} = 0.0327 \quad (4.30)
\]

$a$ and $b$ were derived as before;

parameter $\text{dum}$;

\[
\text{dum} = \frac{\frac{\bar{x}}{1-\bar{x}}}{\bar{x}} = 6.0522 \quad (4.31)
\]
Thus, if the AM-Weather forecast showed Ohio in a high pressure, and the time of the year was winter and it was clear, then the $b$ function was described with the parameters $a = 2.3351$ and $b = 0.3858$ as shown in equations 4.32 and 4.33. These figures now superseded those derived previously for this atmospheric condition, and their graphs are shown in Figures 4.9 and 4.10.
The statistics for the derivation of the curves for low pressure and overcast conditions were as follows:

\[
\bar{x} = 0.2937 \quad \text{(4.34)}
\]

\[
\Sigma x = 9.9870 \quad \text{(4.35)}
\]

\[
\Sigma x^2 = 3.9799 \quad \text{(4.36)}
\]

\[
n = 34 \quad \text{(4.37)}
\]

\[
s^2 = \frac{n\Sigma x^2 - (\Sigma x)^2}{n(n-1)} = 0.0317 \quad \text{(4.38)}
\]

\(a\) and \(b\) were derived as before;
parameter dum;

\[ \text{dum} = \frac{-x}{1-x} = 0.4159 \] \hspace{1cm} (4.39)

\[ b = \frac{\text{dum}}{s^2(\text{dum} + 1)^3} - \frac{1}{\text{dum} + 1} = 3.9147 \] \hspace{1cm} (4.40)

and

\[ a = \text{dum} \times b = 1.6282 \] \hspace{1cm} (4.40)

Thus, if the AM Weather forecast showed Ohio in a low pressure, and the time of the year was winter and there was fog or heavy overcast, then the \( \beta \) function was described with the parameters \( a=1.6282 \) and \( b=3.9147 \) as shown in equations 4.39 and 4.40. These figures now superseded those derived previously for this atmospheric condition, and their graphs are shown in Figures 4.11 and 4.12.
Figure 4.11 PDF for $\beta (1.6282, 3.9147)$

Figure 4.12 CDF for $\beta (1.6282, 3.9147)$
Notice the change in the shapes of the curves when compared to their corresponding curve derived before the 1988 update. β parameters were also derived for the conditions of winter, low pressure, and clear; and winter, high pressure and overcast. They were as follows:

- low pressure and clear: \( a=1.5117 \) \( b=1.4954 \)
- high pressure and overcast: \( a=1.6008 \) \( b=0.8819 \)

These β parameters only serve to illustrate the point of adaption. Within the operating model they would change from day to day as more data was added to the base.

It seems that much work was done to show only four alternative probability curves for the possible solar irradiance transmission ratios for Ohio, i.e., \( k = 1 \) to \( 4 \). It would be advisable to continue the analysis for other years to establish probability curves that have a smaller variance. It is possible that more parameters would have to be incorporated into the analysis so as to minimize the variance of the sample.

**Construction of the outcome evaluation rulebase**

This part of the tree was the most critical and yet it was the most difficult to construct. If a simulation model were available to evaluate the tree and compute outcomes, this would be its place. Such a model did not exist for the cucumber, and so the intuitive model of the grower had to be used instead. The details for this intuitive model were gleaned from the telephone discussions, the video-tape, and the informal discussions with
the expert and the experience of growing the cucumber crop in the greenhouse.

The combination of accepted practice techniques combined with possible new "discoveries" in the way the plant reacted to the solution was most confusing. The crop was grown in an almost zero leachate condition, and for the first time the capability of accurately controlling the input and measuring the output as leachate was available. Eventually a rule-base was constructed that would assess the combination of each recipe proposal with each solar irradiance level and give a crop response function for that combination. This crop response function was described as the probability of obtaining the best crop in terms of quality and yield, given the circumstances prevailing in the decision tree.

The model allocated a crop response function based upon an evaluation of the path taken to each outcome. For example, a recipe comprising medium nitrogen, medium calcium and low potassium being fed to a fruiting crop during a period of low solar irradiance was unlikely to result in producing a good fruiting output because vegetative growth would be enhanced. The probability of producing the "best" crop under those cultural conditions would be about 0.3. That is, a thirty percent chance of producing a "best" crop, or, conversely, a seventy percent chance of producing a bad crop was estimated by a combination of the expert's observations and the final analysis of the person building the knowledge base. The crop response function of that path was allocated a value of 0.3.
The path was dependent upon two items, the nutrient recipe in the decision node and the solar irradiance in the chance node, giving:

\[ u(i,j) = \text{utility function for the } i^{th} \text{ recipe and the } j^{th} \text{ solar irradiance range derived from the historical expertise of growing the crop.} \]

Figure 4.13 illustrates the derivation of the crop response function.

The rulebase which was combined with this crop response function to give the recipes is listed in Appendix F.

**The complete model**

A complete figure showing the relationships between all the parts of the model is shown in Figure 4.14.

To summarize, the recipe(i) selected was the one that had the maximum expected value, \( y(i) \), where:

\[
y(i) = \sum_{j=1}^{3} p_k(j) \cdot u(i,j) \quad (4.26)
\]

where, \( p_k(j) \), (equation 4.2) was the probability of occurrence of the \( j^{th} \) level of solar irradiance predicted from the \( k^{th} \) selection of the \( a \) and \( b \) parameters of the \( \beta \) distribution as selected from the results of the weather forecast, and,
$u(i,j)$ was the utility function derived from the historical expertise of growing the crop using the $i$th nutrient recipe and the $j$th level of solar irradiance.
Knowledge Base for cucumbers

Crop response function derived from a rule-based system which has been learned from a combination of experiments and an expert in the growth of the cucumber

Response node

- $u(i,j)$ Best possible crop
- $1-u(i,j)$ Worst possible crop

Figure 4.13 Derivation of the utility function
Known facts

Items + Range of values

crop type Nitrogen

crop variety Phosphorus

physiological age Potassium
time of day Calcium

temperature Magnesium
relative humidity Sulphur

pH range Nitric acid
EC range Phosphoric acid

Main decision nutrient recipes assembled from pre-prioritized, pre-defined nutrient concentrations and value ranges using intelligent selection guided by the known facts

Feasible Nutrient Recipes

Decision Node (which recipe?)

Recipe 1
Recipe 2
Recipe 3
Recipe 4
Recipe 5
Recipe 6
Recipe 7
Recipe 8
Recipe 9

Figure 4.14 A schematic of the complete model showing the relationships between nodes.
Determination of the distribution function parameters of the solar radiation transmission factor, (0-1), from weather forecasts using an inference engine.

Knowledge Base for cucumbers

Crop response function derived from a rule-based system which has been learned from a combination of experiments and an expert in the growth of the cucumber.

Response node

Potential crop response evaluation

Solar Irradiance Transmission Probability Distribution

Probability of occurrence of the solar irradiance intervals from integration of the probability density function:

- \( p_k(1) \) of \( R_n > 500 \text{ w/m} \)
- \( p_k(2) \) of \( 500 > R_n > 250 \text{ w/m} \)
- \( p_k(3) \) of \( R_n < 250 \text{ w/m} \)

Best possible crop

Worst possible crop
Knowledge Base for cucumbers

- rule 1
- rule 2
- rule 3
- ...
- rule n

Crop response function derived from a rule-based system which has been learned from a combination of experiments and an expert in the growth of the cucumber.

Transmission Probability Distribution

- $p_k(1)$ of $R_n > 500 \text{ w/m}$
- $p_k(2)$ of $500 > R_n > 250 \text{ w/m}$
- $p_k(3)$ of $R_n < 250 \text{ w/m}$

Response node

- $u(i,j)$: Best possible crop
- $1-u(i,j)$: Worst possible crop

Potential crop response evaluation
CHAPTER V

DECISION MODEL IMPLEMENTATION

Introduction

To recap from Chapter II, the decision-making process applied to classes of problems that had the following characteristics:

- identifiable actions that could take place;
- dependence upon probable future occurrences;
- situations that required real-time control;
- the ability to predict outcomes by simulating paths in the tree;
- outcomes that were not necessarily based on economics.

Quality of product, path entropy, environmental impacts and other relevant judgements should be able to be incorporated into the decision making process.

An application

A greenhouse operation required decisions to be made from time to time within the day that would have major impacts upon the final profitability of the enterprise. There were many decisions that needed to be made on a repetitive, short-term, basis that directly affected the final quality and yield of a crop. Examples of these included irrigation quantities,
nutrient feeds, temperature settings, relative humidity settings, ventilation, shading, and control of pests and diseases. One of the objects of this research was to examine a set of those decisions and to see whether or not the computer model would be able to make such decisions and act upon them in a meaningful way.

The following points were considered when applying the model to the problem of plant nutrition in the greenhouse.

- The stochastic parameter was defined as the probability of particular solar radiation transmission levels.

- Definition of the objective function and the control parameters was important.

- The plant had available in the leaf and/or fruit the elements and compounds necessary for optimum use of solar energy at the given environmental conditions.

- How far into the future was it necessary to predict in order to make better decisions at that particular point in time?

- Avoidance of lethal error.

The solar radiation transmission levels have been described in detail in the previous chapter. The objective function was defined using the concept of decision tree path evaluation and coding it in terms of a pseudo utility function as described in Chapter II. The time constant was dictated at the minimum by the time taken by the computer to complete a whole set of
computations and to make the relevant adjustments to the hardware controlling the nutrient injection into the irrigation water. It was dictated at a maximum by the time within which the plant needs to be prepared for the particular event that was to occur in the future such as high or low solar irradiance values. Finally, the problem inherent in growing any plant, that of avoiding a lethal error. The biological system is very sensitive to the long-term lethality of short-term minor adjustments to a nutrition program. The cucumber crop reflected in its growth from day to day those nutritional practices that were implemented 48 days before. A small, but adverse, change in nutritional input to a plant could result some time later in the death of that plant.

The model was constructed to consider all the items discussed above and limits were built into the model so as to ensure non-lethal dosing of the plants. Figure 5.1 illustrates how the different computational techniques were interconnected within this application of the model. For convenience the model was named Aid to Decision Management, (AIDM).
Data retrieval from instruments (dial-up modems) 
Input from Weather Forecasts (TV, Radio) 

Computer simulation of relevant plant growth 
Computation of solar irradiance probability distribution function 

Decision Management Program - AIDM - 

Plant nutrition Inference Engine Subroutine 
Utility Analysis calculation package 

Adjustments to the Nutrient Feed mechanism to maintain optimum nutrient supply. 

Figure 5.1 Layout of the irrigation and nutrient feed decision model
Hardware

The computer selected for development of the software and for use as the decision making computer was an Apple Macintosh. The user interface developed by Apple was deemed important, as the delivery hardware and software had to be easy to use and self explanatory. Final software applications had to be able to be run easily, almost exclusively with the mouse, with a minimum of input from the keyboard and no reference to the manual. Macintosh users would be familiar with such a policy. The Macintosh ROM has been based around event driven programming which was admirably suited for this type of application.

Software

All software written particularly for the decision model was written using Turbo Pascal® by Borland International. Software was written for the following sections of the model:

- operational shell (windowing etc.),
- decision tree shell,
- expert system shell,
- clear sky radiation computation,
- evapotranspiration calculation,
- knowledge files,
• Gamma function,

• Beta function,

• probability density function for irradiance transmittance,

• cumulative distribution function for irradiance transmittance.

Some commercially available software was used for programming, concept testing, communications and presentation.

Programs used for these functions included;

• Programming - Turbo Pascal - Borland International,

• Concept testing - MultiPlan - Microsoft Corporation,

• Communications - Microphone - Software Ventures,

• Presentation - Word 3.01 - Microsoft Corporation,

Cricket Graph - Cricket Software

MacDraw - Apple Computers

MacPaint - Apple Computers.

**Concept testing**

Microsoft MultiPlan® was used to test processes before committing them to code in Pascal. A spreadsheet was built that would take into account the components of a number of commonly used nutrients in
greenhouses. Atomic weights and solution electrical conductivities were taken from the CRC Handbook of Chemistry and Physics, 66th edition. The spreadsheet computed, based upon the injector head settings, the concentration of each component in the irrigation supply line and the electrical conductivity of the final solution. An example of part of the spreadsheet output is shown in Table 5.1 below.

Table 5.1a Solution concentrations from fertilizer amounts and purities.

<table>
<thead>
<tr>
<th>Solution Name</th>
<th>Vol in liters</th>
<th>Fert wt in gms</th>
<th>Vol in US gallons</th>
<th>Fert wt in lbs</th>
<th>Fertilizer Purity %</th>
<th>Sol Conc ppm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nitric Acid</td>
<td>15</td>
<td>1,050</td>
<td>100</td>
<td>58.41</td>
<td>70</td>
<td>49,000</td>
</tr>
<tr>
<td>Phosphoric acid</td>
<td>15</td>
<td>1,267</td>
<td>100</td>
<td>70.47</td>
<td>85</td>
<td>71,783</td>
</tr>
<tr>
<td>Calcium Nitrate</td>
<td>15</td>
<td>4,000</td>
<td>100</td>
<td>222.52</td>
<td>95</td>
<td>253,333</td>
</tr>
<tr>
<td>Potassium Nitrate</td>
<td>18</td>
<td>4,500</td>
<td>100</td>
<td>208.61</td>
<td>100</td>
<td>250,000</td>
</tr>
<tr>
<td>Mono Amm Phosphate</td>
<td>15</td>
<td>1,200</td>
<td>100</td>
<td>66.76</td>
<td>100</td>
<td>80,000</td>
</tr>
<tr>
<td>Potassium Sulfate</td>
<td>15</td>
<td>1,000</td>
<td>100</td>
<td>55.63</td>
<td>100</td>
<td>66,667</td>
</tr>
<tr>
<td>Magnesium Sulfate</td>
<td>15</td>
<td>4,000</td>
<td>100</td>
<td>222.52</td>
<td>100</td>
<td>266,667</td>
</tr>
<tr>
<td>Urea</td>
<td>15</td>
<td>300</td>
<td>100</td>
<td>16.69</td>
<td>100</td>
<td>20,000</td>
</tr>
<tr>
<td>Micro-nutrients</td>
<td>15</td>
<td>357</td>
<td>100</td>
<td>19.86</td>
<td>100</td>
<td>23,800</td>
</tr>
</tbody>
</table>
Table 5.1b Injector head settings giving the concentrations of individual nutrients.

<table>
<thead>
<tr>
<th>Solution Name</th>
<th>Head #</th>
<th>Head Sett%</th>
<th>NO3 mg/l</th>
<th>NH4 mg/l</th>
<th>P mg/l</th>
<th>K</th>
<th>Ca mg/l</th>
<th>Mg</th>
<th>S mg/l</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water Analysis</td>
<td></td>
<td></td>
<td>3.0</td>
<td></td>
<td>0.4</td>
<td>1.8</td>
<td>96.4</td>
<td>34.9</td>
<td></td>
</tr>
<tr>
<td>Nitric acid</td>
<td>2</td>
<td>35</td>
<td>29.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phosphoric acid</td>
<td>1</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Calcium Nitrate</td>
<td>6</td>
<td>30</td>
<td>83.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Potassium Nitrate</td>
<td>7 &amp; 9</td>
<td>15</td>
<td>40.8</td>
<td></td>
<td>113.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mono Am Phosphate</td>
<td>5</td>
<td>0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Potassium Sulfate</td>
<td>3</td>
<td>0</td>
<td></td>
<td></td>
<td>0.0</td>
<td></td>
<td>20.6</td>
<td>27.2</td>
<td></td>
</tr>
<tr>
<td>Magnesium Sulfate</td>
<td>4</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urea</td>
<td>8</td>
<td>0</td>
<td>0.0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Micro-nutrients</td>
<td>10</td>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>daily irrigation Solution E. C.</th>
<th>N as NO3 mg/liter</th>
<th>N as NH4 mg/liter</th>
<th>P mg/l</th>
<th>K</th>
<th>Ca mg/l</th>
<th>Mg</th>
<th>S mg/l</th>
</tr>
</thead>
<tbody>
<tr>
<td>ml</td>
<td>2,440</td>
<td>157.1</td>
<td>0.0</td>
<td>0.4</td>
<td>115.6</td>
<td>215.8</td>
<td>55.5</td>
</tr>
<tr>
<td>per plant</td>
<td>2,897</td>
<td>455.3</td>
<td>0.0</td>
<td>1.2</td>
<td>334.8</td>
<td>625.2</td>
<td>160.9</td>
</tr>
</tbody>
</table>

Communications

The system of communication between the Apple Macintosh, the PRIVA® Universal greenhouse control computer and the Anderson Ratio:Feeder® control unit made use of the RS232 interface between each unit and a telephone modem. This enabled the use of the local telephone exchange as a switching device so that the Macintosh could communicate with the PRIVA® to obtain data about the compartment climate and the local weather situation and then hang up the phone and phone the Anderson injector unit so as to set all the injector heads and initiate the
irrigation cycle. It was decided to use the RS232 standard so as to create a flexible system.

Communications with both the Anderson Ratio:Feeder® and the PRIVA® Universal computer were run at 1200 baud.

A protocol was established for communication with the Anderson Ratio:Feeder® so that present head settings could be dumped to the screen, irrigation water could be turned on and off and individual injectors could be reset.

**The greenhouse climate control computer**

The greenhouse climate control computer was a PRIVA® Universal computer with a modification incorporated in order to access the memory through an RS-232 communications port. This computer controlled the temperature and relative humidity of the greenhouse.

Compartment heating was by gas fired air circulation units and ventilation was achieved by progressive operation of various fans in the end wall of the greenhouse. These were controlled by the PRIVA® Universal computer.

**The nutrient injector**

Some years before the commencement of this development work, the concept of individual nutrient injection into irrigation lines had been proposed by Dr. Bauerle (Horticulture Department, OSU) to the President of H.E. Anderson Co., a manufacturer of injection equipment for water
treatment facilities. The resulting discussions led to the development of an individual nutrient injection system for use within the irrigation systems used in greenhouses. It was based upon the Anderson Ratio:Feeder® injectors widely used by the greenhouse industry.

The Anderson Ratio:Feeder® operated in a positive displacement mode. The pressure of the supply water was used to drive the injector heads in such a way that the injected volume was not affected by variations in water supply pressure.

Standard Anderson injector heads were modified to incorporate a positioning device so that the heads could be remotely controlled. A specialized set of ten injectors was assembled based upon standard Anderson units to provide the injection of concentrate into the irrigation line. The drive unit used was a Ratio:Feeder® Model BRC-1 driving eight model P4HC-J1 injectors and two model P4HC-GL injectors. These injectors were rated at 120 psi and could be varied from 5% to 100% of injected solution.

A photograph of the Anderson Ratio:Feeder® unit installed in the greenhouse is shown in Plate I.

The Irrigation distribution system

Valves were used to control the supply of the irrigation water to different zones of the cucumbers and one emitter per plant was used. The accuracy of supply of the emitters was checked from time to time during the experiment to determine that the flow through each emitter was within an acceptable range about the mean.
A photograph of the mainlines, laterals and emitters of the irrigation supply laid out in the greenhouse is shown in Plate II.
Plate I  Computer controlled Anderson Ratio:Feeder®
Plate II The irrigation supply system mainlines, laterals and emitters
The Greenhouse

The greenhouse was a Rough gutter-connected twin bay unit with heaters and ventilation fans controlled by the PRIVA® Universal computer with sensors for dry-bulb and wet-bulb temperatures. All irrigation cycles were controlled with the Anderson Ratio:Feeder® injector unit as described above.

Plate III shows a schematic diagram of the communication layout between the decision making computer, the PRIVA® greenhouse control computer and the Anderson Ratio:Feeder® unit. Note the use of the telephone exchange to give a multiplexing capability.

Plate IV shows the liquid flows of water and nutrients from the supply systems to the cucumbers in the rockwool bags.
Figure 5.2 Schematic of the communication layout between the decision computer, the control computer and the nutrient injector.
Figure 5.3 Nutrient flows and control paths in the cucumber growth experiment.
CHAPTER VI

OPERATION OF THE MODEL

Flow chart

Figure 6.1 shows a summary flow chart of the model for one decision operation.

At the beginning of the day the grower had to watch the weather forecast on the relevant television channel and then take a walk around the greenhouse, noting anything particular about the crop. On returning to the operations room, the model was started. The model then interviewed the grower about the weather forecast and the crop condition. If the crop condition was unusual, the model ran a nutrient diagnosis procedure (rulebase #4) to establish the cause of the deficiency or toxicity in the crop. Once established, an adjustment was made to the feed file to take this problem into consideration in the following feed program.

The weather forecast input enabled the building of the probabilities of solar irradiance transmission ranges for the coming day as detailed using the f distribution and rulebase #2. The date, latitude and longitude enabled the figure for clear sky radiation to be computed. This figure, together with the probabilities of the transmission ranges gave the probabilities for actual solar irradiance values for the coming day.
Commence decision program

First decision of the day?

yes

no

Crop condition checked?

yes

Input crop condition to crop expert system

compute nutrient feed adjustments

weather forecast checked?

yes

Input weather forecast to expert system

no

check crop condition

look up the previous decision

look up recent radiation history

compute adjustments to previous decision

compute PDF of future radiation

compute future clear sky radiation

get microclimate parameters

continued

Figure 6.1 Flow chart of the model.
Figure 6.1 continued

1. Compute irrigation requirement
2. Allocate decision tree probabilities for radiation intervals
3. Compute utilities for nutrient options and radiation intervals
4. Fold back decision tree to obtain maximum utility
5. Finalize the new decision
6. Incorporate adjustments from previous decision
7. Set the injectors
8. Turn on the water (zone & volume)
9. Predefined waiting time
10. Redefine a and b parameters for β

Decision:
- Yes: End of the day?
  - Yes: Return to beginning
  - No: Redefine parameters for β
- No: Return to predefined waiting time
The microclimate parameters, temperature and relative humidity, in the greenhouse were retrieved from the climate control computer. These, together with the solar irradiance value at the mode of the relevant distribution enabled the computation of the irrigation requirement of the crop.

The maturity of the crop and rulebase #1 defined the nutrient recipe options open to the model for consideration. These options were combined with the irradiance ranges and rulebase #3 to compute the utilities of each possible path of the decision tree. Once the utilities were derived, the cross products of the decision tree were computed and the recipe option with the maximum expected value was selected.

The model then incorporated adjustments from the previous files of surpluses or deficits in the supply and any special nutritional requirements from the diagnosis.

Once the acceptable ranges of the nutrients were finalized, the model computed the settings of the injector that ensured that all nutrients were within suitable limits. The phone connection was then made to the injector and the instruction given to irrigate with the relevant quantity of water and the nutrient settings at the positions required.

Input/Output

The model was constructed in such a way that the operator could input relevant data at convenient times. However, the decision making part of the program was only enabled once all relevant data had been input
to the database. At this point the model computed the irrigation requirement and the optimum nutrient recipe for each hour of the coming day.

An example of the model output for November 16th, 1988, is shown below.

Inputs:

• forecast of high pressure and a clear day in the winter,
• atmospheric pressure of 1010 mb.,
• outside temperature of 60°F and dewpoint temperature of 35°F,
• Greenhouse dry bulb temperature of 72°F and wet bulb temperature of 65°F,
• Cucumber maturity is fruiting.
Outputs:

Irradiance for: 11 16 1988

Clear Sky Rad. per square meter

<table>
<thead>
<tr>
<th>Kj/hr</th>
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Irrigation for: 11 16 1988

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The cucumber growth stage is: flower_to_fruit

recipe selected for hour 6 is 3
Set the nitrogen at: 150_to_200_mg/l
Set the phosphorus at: 40_to_75_mg/l
Set the potassium at: 300_to_400_mg/l
Set the calcium at: 220_to_300_mg/l
Set the magnesium at: 30_to_50_mg/l
Set the sulphur at: 30_to_40_mg/l
Do not exceed an electrical conductivity of 2500_micromhos

recipe selected for hour 7 is 3

recipe selected for hour 8 is 3

recipe selected for hour 9 is 3

recipe selected for hour 10 is 5
Set the nitrogen at: 200_to_250_mg/l
Set the phosphorus at: 40_to_75_mg/l
Set the potassium at: 400_to_500_mg/l
Set the calcium at: 140_to_220_mg/l
Set the magnesium at: 30_to_50_mg/l
Set the sulphur at: 30_to_40_mg/l
Do not exceed an electrical conductivity of 2500_micromhos

recipe selected for hour 11 is 5

recipe selected for hour 12 is 5

recipe selected for hour 13 is 5

recipe selected for hour 14 is 5
recipe selected for hour 15 is 3
  Set the nitrogen at: 150 to 200 mg/l
  Set the phosphorus at: 40 to 75 mg/l
  Set the potassium at: 300 to 400 mg/l
  Set the calcium at: 220 to 300 mg/l
  Set the magnesium at: 30 to 50 mg/l
  Set the sulphur at: 30 to 40 mg/l

Do not exceed an electrical conductivity of 2500 micromhos

recipe selected for hour 16 is 3

recipe selected for hour 17 is 3

recipe selected for hour 18 is 3.

Explanation of output

The irradiance figures were computed and tabulated from 6am. to 6pm. in kilojoules per hour per square meter and watts per square meter at the cover of the greenhouse on a horizontal surface. The photosynthetically active radiation (PAR) was given in watts per square meter after accounting for the attenuation and reflection by the greenhouse structure and multiplying by a factor of 0.45 to give PAR from the total spectrum. Examination of the β distribution for the day applied to each hour gave the probabilities of the PAR being less than 50, 50 to 150 and more than 150 watts per square meter for each hour in this output.

Irrigation requirement was computed from the combination model and listed for each hour from 6am. to 6pm. The stage of growth of the plant was determined and then the cross products of the decision tree evaluated to
give the recipe recommendation for each hour. The first hour of a recipe change specified the constituents of the recipe as well as a recommended maximum for the electrical conductivity of the solution.

The recipe recommendations were implemented by setting the Anderson Ratio:Feeder® to the recipe selected by adjusting the feed ratios of each injector head. The quantity of water required was defined by totalling the volumes for the hours in which that recipe applied. In the example above, recipe 3 would be applied between the hours of 6am. and 10am. in a quantity of water totalling 0.42 liters per square meter of the greenhouse. At 10am. the model output was used to set the injectors to give recipe 5 and irrigate 1.15 liters per square meter of the greenhouse, being the total irrigation required between 10am. and 3pm. when the recipe needs to be changed back to recipe 3.
CHAPTER VII

RESULTS AND CONCLUSIONS

Results

Recall that the objective of the research was to construct a decision making model that would exploit the advantages of both decision analysis and expert systems in such a way that the model would make better decisions than those made by either concept used alone.

The combination of decision analysis and expert systems did enable the construction of a decision model that accomplished what neither tool could have achieved alone. The ability to use intuitive modeling provided by the expert combined with the use of solar irradiance probabilities and crop response functions in the decision analysis model gave a more flexible and adaptable model, which had the pliability to be further refined as data logging and scientific advances permitted. The model was successfully applied to the problem of nutrient selection in growing a greenhouse vegetable.

The requirements of the model and a discussion of how those requirements were met is presented below.

- that the model would operate in real time.

The use of probabilistic forecasts of solar irradiance enabled the nutrition applications to be made in such a way that the future, short-term,
requirements of the crop were met within the context of the microclimate prevalent at the time of application. This use of prediction to give real time control so that the plant had the correct nutrition available at the time it was required, rather than some hours later, was one of the unique aspects of the model. This was enabled by the use of the solar irradiance forecasts and probabilities combined with the probabilistic outcome of a "best crop" by the nutritionist under the prevailing circumstances. The combination of the two systems, decision analysis and expertise, was essential to achieving this goal of real time control.

- that the model incorporate probabilistic predictions for use in making the decision.

The use of the β distribution to model future occurrences of the levels of solar irradiance for the coming day was an essential part of the model. This enabled the application of the model in the circumstance described so that the crop was fed the nutrients that it required in the near future. It facilitated the ability to control in real time from the aspect of the nutrition of the crop.

- that the model select the most pertinent options from a variety of possibilities.

Decision analysis alone could not define the options that could be considered under specific circumstances. Chemical and resource inputs were used to define the decision options which were assembled as combinations of nutrient concentrations, or recipes, under the guidance of
an expert in plant physiology. These options depended upon the growth stage of the plant and the nutrients available to the grower. Both direct computations and the grower's preferences for particular nutrients were considered in the selection of possible options open to the decision model.

- that the model will incorporate non-monetized outcomes.

The use of expertise and crop response functions permitted the estimation of outcomes which combined the quality and yield of the crop. This function was used by the decision tree core to compute the expected values of the different recipes so as to select the recipe for that particular hour.

- that the model will enhance results by adaptation.

The updating of the solar irradiance probability prediction by the incorporation of the data gathered from day to day to modify the distribution enabled the convergence of the model in the aspect of adapting to the locale in which the model was operating. Incorporation of any new discoveries into the model was made easy by the use of rulebases which were updated by the writing of new rules and the modification of the old ones. These rule changes reflected new knowledge being gained by researchers in the area of application and were ongoing during the time of the research.
Conclusions

Convergence

An important item with any model is one of convergence. Did the model make the selection of nutrients any more accurately than the equipment presently available, and will the model converge to optimum answers as it is improved in the future?

Application of the model showed a need to change recipes during the day as the solar irradiance levels changed. This alone was a major improvement over present systems. The model incorporated many more items in its decision making process than did any nutrient equipment and/or software available and used in commercial greenhouses at the time. The fact that the model adapted to its local solar irradiance conditions by modification of the \( B \) distribution meant that it selected nutrient recipes that were more appropriate to the needs of the crop. Thus the model showed a tendency to converge as the variance of the probability distribution of the solar irradiance became less as time passed. The model also enabled more appropriate feeding of the crop as the solar irradiance changed during the day.

Derivation of the rulebases

A variety of techniques contributed to the success of the rulebase derivation. In particular, the telephone interviews enabled much information to be gathered in a short time. They required an intensive effort by both the knowledge base builder and the expert, forcing the expert
to think carefully about the kinds of questions posed to the operator in order to obtain the correct answer. For example, it was decided that a part of any expert system that judged a crop's condition by leaf color absolutely required a green color chart so that both parties could be sure exactly what was meant by the term "light green." In addition to the telephone interviews, general discussions with the expert proved to be essential and enlightening, and many follow-up meetings had to be held to clarify points of discussion. Examination of the video-tape made of the expert's reaction to the crop after the experiment was also extremely useful. None of the techniques superseded any of the others, rather, they all served to supplement each other, building a more comprehensive set of rules.

Recommendations and future research

Model development

Expansion of the model to include multiple chance nodes so that disease and pest strategies can be incorporated would be extremely useful. The use of the model with integrated pest management (IPM) techniques needs to be studied so as to make maximum use of the model's potential.

Model applications

Use of the model in controlled environment agriculture for the growth of cucumbers is possible at this moment. Future crops will be added in the near future. However, as the model will be undergoing further development and validation, close cooperation with the author is advised.
The model could be used to test plant responses under particular conditions. Plant nutritionists, pathologists and entomologists could hypothesize about possible chemical, disease and pest interactions within plants and between them and their environment, and incorporate those hypotheses in the model. Decisions taken by the model during the growth period would be consistent with the hypothesized rulebase.

Model availability

The author may be contacted at the following address to discuss possible uses and further development of the model. The model is currently run on a Macintosh computer and is being modified for use with an MS-DOS machine.

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Ohio Agricultural Research and Development Center,
Wooster
Ohio 44691.
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Roller, Warren L. Discussions with author, 1988, Wooster, OH.


APPENDIX A

REVIEW OF TECHNOLOGIES

Introduction

The problems of the supply of nutrients to a crop grown under controlled conditions in a soil-less culture have been investigated since the concept of growing hydroponically was seriously proposed in the 1950's. Much work has been done on nutrient supply and systems to distribute those nutrients (Adams 1980, Sonneveld 1985).

One point that was very evident to a newcomer in the area was that nutrient selection and feeding at different periods in the growth of a crop and under different ambient conditions required considerable expertise on the part of the grower if the crop was to be of high quality and consistent in output. This applied to any crop. It was particularly so in a soil-less culture and many organizations growing hydroponically have had considerable trouble with disease and nutrient control. In order to grow successfully the combination of water chemist, plant nutritionist, weather forecaster, disease analyst, chemical engineer, and agricultural engineer seemed to be required all rolled into one person.

The recent development of a single element nutrient dosing injector that would accurately inject nutrients into an irrigation supply system introduced the concept of the possibility of changing nutrient mixtures at very short notice. Remote control of the injector heads meant that
Decision Making

In analyzing the requirements of a system that would aid in the task of feeding individual nutrients to a crop, the technologies that seemed to be necessary were those of being able to make decisions within a scenario of restricted resources, and being able to formulate the bounds within which those decisions were to be made. The nutrients available, the crop, its environment and the application system defined the bounds of possible options. From the possible options a method had to be found to select the option that would produce the best possible crop under the prevailing conditions.

Frohman (1987) proposed a generic step by step process to reach the best solution to both technical and nontechnical problems. While a simple aid, this approach was a useful one for repetitive decisions. His process was:

1. clarify the goal and criteria
2. define the problem
3. list all possible solutions
4. evaluate the alternatives
5. select a solution
6 plan implementation

7 implement and review.

This was very similar to the process used in the model building concept used in this dissertation, and in the concepts used by decision makers in the formulation and use of decision trees in science of decision analysis.

**Decision Analysis**

The science of decision making in which the complex mechanisms used by the mind are reduced to trees, nodes, probability functions and utilities has been investigated for many years (Pratt 1964, Raiffa 1970, Cohan 1984). This science has been used in such diverse disciplines as law (Schum, Schum and Martin, von Winterfeldt and Edwards), siting of large complexes such as airports (Keeney 1976, de Neufville 1985), and capital investment decisions (Hax and Wiig 1977).

The introduction of the single element nutrient injector has changed the nature of the decisions to be made in the supply of nutrients to crops. Until now the grower was limited in the choices available for changing nutrient feeds once the feeding system had been installed and nutrient solutions mixed. The individual nutrient injector changed that in the same way as new technologies change the nature of decision making in manufacturing (Fraser, 1986). New ways had to be found to cope with the problem of making decisions within the context of this new technology.
The concept of using decision analysis in conjunction with the techniques of heuristic programming from Artificial Intelligence has been proposed by Lehner, Probus and Donnell (1985) and Langlotz, Fagan, Tu, Sikic and Shortliffe (1986). The latter provided for the combination of heuristics from therapy planning strategies feeding into a decision tree which delineated options which were then ranked by evaluating the tree. The use of decision trees necessitated the ability to predict probabilities of future events. This required a knowledge of the event and an understanding of probabilities.

**Probability**

Probability theory, when used correctly, is sufficient for the task of reasoning under conditions of risk and uncertainty (Cheeseman 1985, Adams 1976, Schum 1986). Probability theory and application have come under attack from some scientists claiming to invent new ways of taking uncertainty into consideration (Shortliffe 1975, Zadeh 1980). These contentions have been strongly refuted (Cheeseman, 1986; Schum, 1986). Models using Bayesian logic have been successfully built and operated (Duda, 1979, Cohan 1984).

All probabilities are conditional upon the information available on the subject. The basic problem that any decision approach must deal with is that the available information is not sufficient to determine any particular conditional probability. The probability space is usually underconstrained by the known probabilities making it impossible to calculate directly any particular conditional probability.
The maximum entropy assumption shows that the initial best conditional probability is the one that has the maximum number of possible worlds consistent with the known information (Cheeseman 1983). This works well for objective probabilities. Subjective probabilities should be treated the same way, but people are not good estimators of probability (Cheeseman 1984). Subjective probabilities are present in all statistical assessments, even those that are supposedly totally objective (Berger, 1988).

**Inference**

The inferring of new information from old is done by people everyday. But is the information really new? It is information that results, in the inferrers opinion, from previous experiences in similar scenarios. This means that a person who can make inferences must have some experience.

Inference has been studied in a variety of subjects from law (Schum 1979-1986) to searching for mineral deposits (Duda 1979) and medical diagnosis (Shortliffe 1975).

Anyone who has served on a jury has had their reasoning ability tested. Passing sentence on one's fellow man is not to be taken lightly. For this reason the study of inference by jurors is significant (Schum 1981, Schum and Martin 1982, von Winterfeldt and Edwards 1986). These authors found that consideration of a complex problem was deemed more easy by the participants if the problem was broken down into parts, rather than being digested as a complex whole.
Much emphasis has been placed on the development of systems to incorporate these inference schemes into computer programs (Baur 1987). The concept of inference is complex, but it has been analyzed mathematically (Prade 1983) so that it may be used in computer programs. Its use can be regarded as a step towards the incorporation of conceptual reasoning into computer programs.

**Development of expertise**

The Dreyfus brothers, in their book, "Mind over Machine", delineated the five stages of development from novice to expert. They are briefly discussed below:

**Novice**

The novice works with "context-free" rules, manipulating them by information processing. There is no prior knowledge or experience that can be used as guidance so absolute rules lead to absolute answers.

**Advanced beginner**

Experience in the real world situation improves the performance of the novice to a marginally acceptable level. Skills become evident as the novice learns. Through practical experience the advanced beginner perceives things as being similar to prior examples. This is the introduction of the "situational" element as opposed to the information processing element.
Competent

Eventually the "context free" and "situational" elements in the real world become overwhelming. To cope in such a situation, people learn to adopt an hierarchical procedure of decision-making akin to filtering. Performance is simplified and improved by only examining the small set of factors that are relevant to the situation. This has been found to be beneficial in the legal context (Schum 1981, von Winterfeldt 1986).

Proficient

The jump to proficiency incorporates a major change in approach to the new skill. Up to this point, the person has made conscious choices of goals and decisions after reflecting upon various alternatives. The proficient performer is deeply involved in the task at hand. Events are filtered and acted upon with relatively little analytical thought. They are being "sensed" rather than measured. This can be regarded as the beginning of intuition, or the ability to use patterns without decomposing them into their individual elements. The Dreyfus brothers call this "holistic similarity recognition." They state: "Intuition ... is neither wild guessing nor supernatural inspiration, but the sort of ability we all use all the time as we go about our everyday tasks."

Expert

The expert generally knows what to do based upon mature and practiced understanding. When deeply involved in coping with the environment he does not see problems in some detached way and work at
solving them, nor does he worry about the future and devise plans. An expert's skill has become so much a part of him that he is no more aware of it than he is of his own body.

**Artificial Intelligence**

If a computer could help with the competent pieces of our jobs, would this release us to make the jump to more intuitive thinking? Could we become tacticians instead of operators?

This type of computer program has been formulated by the Artificial Intelligence community to help with solving problems more quickly. It is known as an expert system, so called, because the data, in the form of a rulebase, is usually drawn from an expert. The rulebases are manipulated by a computational concept known as an inference engine (Shortliffe and Buchanan 1975, Adams 1976, Langlotz, Fagan, Tu, Sikic and Shortliffe 1986, Pednault, Zucker and Muresan 1981).

However, there are some dissident voices in the scientific community about the application of expert systems (Dreyfus and Dreyfus 1986, Denning 1988).

Roger Shank stated in Waterman, 1986: "A.I. would have a fairly difficult time justifying itself as a scientific discipline." He said there was no agreement on what the issues were. He felt that learning was the central issue, yet general learning programs were not even on the artificial intelligence horizon. He stated that: "expert systems are cut off from common sense and from change and that present (1986) research in artificial
intelligence avoids the problems of common sense understanding and
temporal change." However, he acknowledges that knowledge engineering
is now a booming field.

Concern about the problems of blind faith being placed in expert
systems has also been raised (Denning, 1988). Blindness inherent in system
design precludes designers from making more robust systems. In the
domain of action, a person reacts to events by bringing know-how into
action without conscious thought. One does not have occasion to bring
thought to bear on events until a "breakdown" occurs - an event that
interrupts the flow of action towards one's goals. Description is an account
of action as it appears to an observer. The knowledge engineer attempts to
describe an expert's action in the terms of a rulebase. Something is lost in
the translation of action into a description of what happened. The domain
of description does not give one full access to the domain of action. That is
why you can only examine in detail your own decision making attitude
because you know what you did and why you did it.

Blindness in system design cannot be overcome simply by putting all
the rules into one large database where they can be combined in new,
unexpected ways. Denning states, "So ingrained is the traditional view of
problem-solving as the cornerstone of intelligence that new distinctions,
such as the domains of description, action, and commitment, seem strange
and hard to grasp. And yet coming to grips with them will enable designers
to overcome blindness in expert systems and is likely to produce new
successes in artificial intelligence."
A similar attitude is taken by the proposal that the analysis, design and implementation of expert systems need to be carried on at a much higher level of abstraction (Chandrasekaran 1985). At this level, the knowledge level, interesting similarities between expert systems come to light. Chandrasekaran hypothesizes that complex tasks can be knowledge engineered successfully by using decomposition from complex into generic tasks.

Development

While considerable work has been done on the incorporation of rules into computer programs, it is acknowledged that the acquisition of those rules from the expert is complex (McCoy and Levary 1988). Some guidance has been provided, but the guidance itself is generic and many specifics are omitted (Hayes-Roth 1983). There is the problem that the expert system does not learn in and of itself (Schum 1986), so it cannot progress.

Many authors placed emphasis upon the close cooperation required between the experts and programmers if an expert system was to have any hopes of even marginal success. "When choosing project personnel, good interpersonal skills are just as important as technical skills" (Teschler, 1987).

Adaptive control

Perhaps expert systems developers can learn from the world of adaptive control. Adaptive system characteristics are fundamentally different from those of conventional feedback systems because they incorporate a modification process akin to learning (Ogata 1970).
Adaptive control systems are designed to modify the control signal as the system environment changes so that performance is always optimal. A system which is capable of recognizing the familiar feature and patterns of a situation and which uses its past learned experiences in behaving in an optimal fashion is called a learning system. A learning system is a higher level system than an adaptive system. Control systems can be divided into four basic hierarchy levels (Ogata):

1. open loop
2. closed loop
3. adaptive loop
4. learning loop

Each level is responsive to a performance index or control error measured at the next lower level.

A learning system responding to a familiar situation will not require identification of the system. The approach to the design of such a system is to "teach" the system the best choice for each possible situation. Once the system has learned the optimal control law for each possible situation it may operate near the optimal condition regardless of environmental changes.

The distinction between learning and adaption is an important one. Using the same rules to process more data and come to a new conclusion is adaption, not learning. The model can adapt by analyzing more data gathered on solar irradiance, but the rules by which those data are gathered
and analyzed can only be changed by the programmers and/or the scientists working on the problem.

The adaptive control system has some deficiencies when the problems of future occurrences and probabilities arise. There is the necessity to compare "with the optimal characteristics", but what if the characteristics do not change before the next decision is taken? The system cannot anticipate possible upcoming scenarios. Some of the features of the adaptive control model are applicable to the proposed model, in particular the modification of a decision as a result of performance index evaluation and the issuing of an instruction to a controller. However, the evaluation of the performance index is complex.
APPENDIX B

GROWING THE CROP

Sequence of events

196 cucumber seeds of the variety "Mustang" were started in rockwool cubes on December 26th, 1987, in anticipation of moving them to the greenhouse during January. Unfortunately the prior experiment remained in the greenhouse until the end of January and so the move to the greenhouse did not take place until February 8th (Day 39). 144 plants were established in the greenhouse with 80 plants in the center for observation and 64 as guard row plants. The plants were grown on rockwool bags with two plants per bag. Irrigation was provided through a drip system fed by the injector. The plants were grown for a total period of 52 days and removed from the greenhouse on April 1 (Day 92). The layout is shown in Figure B.1, with a photograph of the layout in Plate III.

The irrigation schedule is shown in Figure B.2 in liters per plant against the Julian day. Notice the increase in irrigation supply from day 75 onwards. Fruit began to multiply from day 71, and picking started on day 75. The startup of the crop was plagued by problems due to the lack of experience of the novice grower. Many fruits aborted early on as they had not been trimmed from the plants as was done in normal growing practice.
Figure B.1 Layout of the cucumbers in the greenhouse.
Plate III Photograph of the layout in the greenhouse showing plants and irrigation scheme.
One of the problems associated with developing prototype equipment at the same time as doing an experiment is shown on days 63 and 64. A drain valve was inadvertently left open on day 63, allowing all irrigation water supplied to go down the drain. This was discovered early in the irrigation cycle on day 64 and rectified. Thus the irrigation on those days was down. Once the cultural practices of the novice grower had been improved, the crop became more healthy, producing fruit at a regular pace and maintaining a more uniform internode length.

**IRRIGATION SCHEDULE**

![Irrigation Schedule Graph](image)

Figure B.2 Graph showing the irrigation schedule followed in the greenhouse.
The method of water potential adjustment has been used by growers as a nutrient control method in the past, but it was useful only if the uptake of nutrients is passive. In fact, nutrients were taken up actively by the plants. For example, in the experiment performed to obtain the growing expertise for this model, it was found that if the crop required water (days 72 to 80) it took it regardless of the nutrient concentration. In fact the leachate from the rockwool bags increased in concentration during this time showing that the crop was selectively taking water and leaving nutrients. The following figures reflect data obtained from laboratory analyses of irrigation water and leachate from the rock wool growth media. These analyses were done twice a week giving the points on the graphs.

Figures B.3 to B.6 illustrate the changes in the supply water and the leachate of the most important nutrients during the growing period. Notice the increase in leachate concentration in the graphs between days 72 and 75. A comparison in the difference between the leachate slope and the supply slope was an indication of the plant's preference for water. It was not taking up nutrient at this time, even though the nutrient was present in increasing quantities in the supply water. The exception was calcium. Calcium was taken up in the xylem in the cucumber plant. All other nutrients shown here were taken up in the phloem. These graphs showed a distinct selection procedure occurring in the plant at this time. Fruiting expansion commenced in earnest on the plants during these days. The slope differences as percentages of the average fed on each were as follows:

\[
\text{nitrogen} - \frac{28.75}{200} = 14.4\% \text{ increase}
\]
phosphorous - \[ \frac{12.75}{65} = 19.6\% \text{ increase} \]
potassium - \[ \frac{60}{360} = 16.6\% \text{ increase} \]
calcium - \[ \frac{5}{140} = 3.6\% \text{ increase} \]

Figure B.3 Graph of Nitrogen concentrations during the growing period.
Figure B.4 Graph of Phosphorous concentrations during the growing period.

Figure B.5 Graph of Potassium concentrations during the growing period.
Estimated vs Applied

The following graphs show the estimated and applied values for the variables concerned plotted against the Julian day of 1988. The estimates were from the spreadsheet computations and were based upon molecular weights and electrical conductivities from the Handbook of Chemistry and Physics. All samples were analyzed in the Research Extension Analytical Laboratory (R.E.A.L.) at the O.A.R.D.C.

Errors could be introduced by impure nutrient mixes, incorrect weighing of the nutrients and inaccurate sample analysis. In some cases the error in the estimate was quite large. For example, phosphorous showed a consistent underestimate. It was likely that these errors were caused by incorrect weighing of the original salts for mixing in the solution. Often the
trend was correct, showing a consistency in the computation and the sample analysis. The nutrient solutions were replenished during the experiment, but some elements were supplied from more than one source (potassium came from potassium nitrate, head #7 and potassium sulfate, head #5), and some sources were replenished three times and some were not replenished. It was probable that, with more care, the estimated and measured concentrations would have a smaller error. Nutrient solutions supplied in premixed form, as is done in Holland, would have aided significantly in the reduction of this error.

**Figure B.7** Electrical conductivity of the nutrient solution.
Figure B.8 Nitrogen concentrations of the nutrient solution.

Figure B.9 Phosphorous concentrations of the nutrient solution.
Figure B.10 Potassium concentrations of the nutrient solution.

Figure B.11 Calcium concentrations of the nutrient solution.
Applied vs Leachate

The graphs of applied solution superimposed upon leachate solution for each entity show the accumulation or depletion of nutrients in the rockwool block. Electrical conductivity is a measure of total salts in solution, and although it gives some indication of the overall accumulation or depletion in the block, it cannot be used as a sole means to judge whether or not a particular nutrient should be increased or decreased in the supply solution. The days 71 to 75 should be noted. Accumulation of all the nutrients in the block was noticed at this time. This was the time when the plants were beginning to produce fruit in quantity.
Figure B.13 Electrical conductivity of the nutrient solution and the leachate.

Figure B.14 pH values of the nutrient solution and the leachate.
APPENDIX C

THE β DISTRIBUTION

Description

The family of beta densities is a two-parameter family of densities that is positive on the interval (0, 1) and can assume quite a variety of different shapes. The beta probability density function has the property of totalling unity when integrated from 0 to 1. It was deemed the most appropriate function to model the probability distribution of a set of data. It has the flexibility required to reflect the variance of a set of data, and it is unimodal so that a local maximum may be established.

If a set of data is found to be bimodal or multi-modal, then it is most probably insufficiently described. The correct priors should reduce the function to a unimodal one. Thus the β distribution was selected as the distribution to describe the data provided that a sufficient number of priors was used.

In the model proposed by Mustacchi, Cena and Rocchi (1979) the probability density functions of solar radiation were bimodal, but they were only considering sectioning the year by summer, winter or the whole year. No other priors obtained from weather forecasts such as weather front positions and locations of high and low pressures were considered by them.
In general, the $\beta$ distribution is described as follows:

$$\beta(a,b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}$$  \hspace{1cm} (C.1)

where the $\Gamma$ function is:

$$\Gamma(t) = \int_0^\infty x^{t-1} e^{-x} \, dx, \quad t > 0$$  \hspace{1cm} (C.2)

The $\beta$ probability density function, PDF is:

$$f(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1}(1-x)^{(b-1)}, \quad x \in (0,1)$$ \hspace{1cm} (C.3)

with $a > 0$ and $b > 0$.

The $\beta$ cumulative distribution function, CDF, is the integral of this between chosen limits, that is:

$$\int_{\min}^{\max} f(x) \, dx = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \int_{\min}^{\max} x^{a-1}(1-x)^{(b-1)} \, dx$$  \hspace{1cm} (C.4)

The various characteristics of the $\beta$ function are as follows:

the mode,

$$c = \frac{a-1}{a+b-2}$$  \hspace{1cm} (C.5)

the mean,

$$\mu = \frac{a}{a+b}$$  \hspace{1cm} (C.6)
and the variance,
\[ \sigma^2 = \frac{ab}{(a+b+1)(a+b)^2} \]  

(C.7).

**Derivation of a and b parameters**

In order to use the \( \beta \) distribution it was necessary to derive the two parameters, \( a \) and \( b \), used in the function. This was done as follows.

Using the sample mean \( \bar{x} \) and the sample variance \( s^2 \) as estimates of \( \mu \) and \( \sigma^2 \), define a parameter \( \text{dum} \), such that:

\[ \text{dum} = \frac{\bar{x}}{1 - \bar{x}} \]  

(C.8)

Now, from the definition of the mean, \( \mu \), equation F.6 above,

\[ a = \text{dum} \times b \]  

(C.9)

Using the definition of \( \sigma^2 \) (equation F.7 above), \( b \) can be derived from:

\[ b = \frac{\text{dum}}{s^2(\text{dum} + 1)^3} \times \frac{1}{\text{dum} + 1} \]  

(C.10)

Thus, knowing the sample mean and the sample variance of a set of numbers between zero and one, the \( \beta \) parameters, \( a \) and \( b \), could be derived to give the \( \beta \) function for the set.
APPENDIX D

CLEAR SKY IRRADIANCE MODEL

Model history

The solar radiation model used in the decision model was assembled using the notes and work from a course by Dr. A. John Arnfield of Ohio State University on microclimatology. A computer program written by Dr. Arnfield for distribution at the annual meeting of the Association of American Geographers on April 23rd, 1984, entitled "Surface climate simulation model. Level IV: Radiative-Conductive-Convective equilibrium (moist surface)" and the paper by Davies and Hay, 1980, were also used for reference.

Model construction

The distance from the sun to the earth changes during the year. The earth rotates about an angled axis at a rate that is not constant and the atmosphere changes from minute to minute. All these factors and more had to be considered in the computation of the radiation received at the earth's surface from the sun. The model was constructed to take account of these and other items as follows.

Extra-terrestrial solar irradiance was computed from the radius vector of the sun, the cosine of the solar zenith angle and the solar constant. The zenith angle is a function of the latitude of the site, the solar declination and...
the hour angle, or time of day. The time of day was expressed in solar time, and that changes from day to day by the ephemeris of the sun.

Equation D.1 gives the derivation of $K_{EX}$, the extra-terrestrial solar irradiance for a given place and time.

$$K_{EX} = I_0 \left( \frac{d}{d} \right)^2 \cos(z) \hspace{1cm} (D.1)$$

where

$$\cos(z) = \sin \phi \sin \delta + \cos \phi \cos \delta \cos(H) \hspace{1cm} (D.2)$$

and

$$I_0 = 1353 \text{ (w.m}^{-2} \text{)}$$

$$\left( \frac{d}{d} \right) = \text{ratio of the mean sun distance to the actual sun distance on that day}$$

$$\phi = \text{latitude}$$

$$\delta = \text{solar declination}$$

$$H = \text{hour angle which included the ephemeris of the sun.}$$

Once the extra-terrestrial irradiance was established an account was made of different parts of the atmosphere that absorbed and/or scattered the incoming radiation.
Attenuation

Radiation passing through the atmosphere is attenuated by water, carbon dioxide, ozone, nitrogen, oxygen, dust and clouds. This attenuation occurs as a function of the gas or particles and the wavelength of the radiation. Different wavelengths are attenuated as follows:

- Wavelengths of less than 0.12\(\mu\text{m}\) are removed in the thermosphere by oxygen, nitrogen and photoionization,
- Wavelengths from 0.12\(\mu\text{m}\) to 0.18\(\mu\text{m}\) are attenuated by the photodissociation of oxygen in the stratosphere,
- Wavelengths from 0.18\(\mu\text{m}\) to 0.34\(\mu\text{m}\) are attenuated by ozone and photodissociation of oxygen,
- Wavelengths from 0.34\(\mu\text{m}\) to 0.70\(\mu\text{m}\) are not significantly absorbed, and,
- Wavelengths from 0.70\(\mu\text{m}\) to 4.0\(\mu\text{m}\) are primarily absorbed by carbon dioxide and water vapor.

Scattering

Scattering comes in two primary forms, Rayleigh scattering and Mie scattering. Rayleigh is very strongly wavelength dependent being approximately proportional to \((\text{wavelength})^{-4}\). It is symmetrical in that similar amounts of radiation are scattered both forwards and backwards. When Rayleigh scattering dominates, the sky will be blue. Mie scattering is
due to particles and aerosols and is approximately independent of wavelength. It is primarily forwards oriented. When Mie scattering dominates, the sky will be white.

Attenuation in the model

The model defined four parameters that would attenuate irradiance so that the clear sky irradiance could be computed from $K_{gx}$, the extraterrestrial irradiance. They are listed below.

$T_o(u_o,m)$ - Transmission after absorption by ozone. This was a function of the thickness of the ozone layer, $u_o$, and the relative optical air mass, $m$, that the ray passes through. $m$ was a function of the solar zenith angle.

$T_R(m)$ - Transmission after Rayleigh scattering. This was a function of the relative optical air mass, $m$, alone.

$a_w(u_w,m)$ - Absorption due to water vapor. This was a function of the precipitable water, $u_w$, in the atmosphere and the air mass, $m$. It was not to be confused with cloud cover. It was the amount of water present in the atmosphere at all levels.

$T_a(m)$ - Transmission after attenuation by aerosols. This was a function of the air mass.

Global shortwave radiation is composed of the solar direct irradiance, which is the component that has not been absorbed or scattered, and the diffuse irradiance, which is the component that has not been absorbed, but
has been scattered down. Diffuse irradiance arrives at a point from a solid angle of $2\pi$, that is all over the hemisphere.

**Solar direct irradiance**

The direct irradiance received at the earth's surface was expressed in equation D.3.

\[
S = K_{EX} \left[ T_0(u_o m) \times T_R(m) - a_w(u_w m) \right] \times T_a(m) \quad \text{(D.3)}
\]

where

$u_o$ was read from Table D.3 which gave a value in mm. for the ozone thickness over the tropics, the mid-latitudes and the polar regions for summer and winter, and, $m = \sec(z)$, where $z$ is the solar zenith angle (Davies and Hay 1980).

<table>
<thead>
<tr>
<th></th>
<th>summer</th>
<th>winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>tropics</td>
<td>2.3</td>
<td>2.3</td>
</tr>
<tr>
<td>mid-latitudes</td>
<td>3.1</td>
<td>3.9</td>
</tr>
<tr>
<td>polar</td>
<td>3.4</td>
<td>4.5</td>
</tr>
</tbody>
</table>
To compute the absorption of the radiation by the ozone layer, the following equations were used:

for ultra-violet

\[ a_o^{uv} = \frac{0.1082 u_o m}{(1 + 13.86 u_o m)^{0.805}} + \frac{0.00658 u_o m}{1 + (10.36 u_o m)^3} \]  

(D.4)

for the visible

\[ a_o^{vis} = \frac{-0.002118 u_o m}{1 + 0.0042 u_o m + 3.23 \times 10^{-6} (u_o m)^2} \]  

(D.5)

then,

\[ T_o(u_o m) = 1 - a_o^{uv} - a_o^{vis} \]  

(D.6)

Transmission after Rayleigh scattering is complex. Sellers gives it as:

\[ T_R(m) = \frac{\int_0^\infty I_\lambda e^{-T_{\lambda R} m} d\lambda}{1353} \]  

(D.7)

where \( I_\lambda \) is the spectral radiation intensity at wavelength \( \lambda \) and \( T_{\lambda R} \) is the atmospheric optical depth. These figures have been computed and tabulated for various air masses, m (Davies and Hay 1980). In the model, the
figures were looked up from a table which was stored as a vector and then used in an algorithm to derive $T_R$. Table D.4 shows the numbers that were used in the model.

Table D.4 $T_R$ factor as a function of $m$.

<table>
<thead>
<tr>
<th>m</th>
<th>$T_R$ factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.8973</td>
</tr>
<tr>
<td>2</td>
<td>0.8344</td>
</tr>
<tr>
<td>3</td>
<td>0.7872</td>
</tr>
<tr>
<td>4</td>
<td>0.7493</td>
</tr>
<tr>
<td>5</td>
<td>0.7177</td>
</tr>
<tr>
<td>6</td>
<td>0.6907</td>
</tr>
<tr>
<td>7</td>
<td>0.6671</td>
</tr>
<tr>
<td>8</td>
<td>0.6463</td>
</tr>
<tr>
<td>9</td>
<td>0.6276</td>
</tr>
<tr>
<td>10</td>
<td>0.6108</td>
</tr>
<tr>
<td>11</td>
<td>0.5955</td>
</tr>
<tr>
<td>12</td>
<td>0.5815</td>
</tr>
<tr>
<td>13</td>
<td>0.5686</td>
</tr>
<tr>
<td>14</td>
<td>0.5566</td>
</tr>
<tr>
<td>15</td>
<td>0.5455</td>
</tr>
<tr>
<td>16</td>
<td>0.5351</td>
</tr>
<tr>
<td>17</td>
<td>0.5254</td>
</tr>
<tr>
<td>18</td>
<td>0.5162</td>
</tr>
<tr>
<td>19</td>
<td>0.4919</td>
</tr>
</tbody>
</table>

The algorithm used to derive $T_R$ was as follows:

If $m > 18.8$, then $T_R = 0.5093$,

otherwise,
\[ T_R = T_R \text{ factor}(\text{int } m) - (T_R \text{ factor}(\text{int } m) - T_R \text{ factor}(\text{int } m+1)) \times \text{fract } m \]  \hspace{1cm} (D.8)

where

\text{int } m \text{ was the integer portion of } m, \text{ and}

\text{fract } m \text{ was the fractional portion of } m.

\[ aw(u_w m) \]

Attenuation due to precipitable water, \( a_w \) was first corrected for
temperature, \( T \), and pressure, \( p \), as follows;

\[ (u_w m)' = (u_w m) \left( \frac{p}{p_0} \right)^{\frac{3}{2}} \left( \frac{273}{T} \right)^\frac{1}{2} \]  \hspace{1cm} (D.9)

where,

\[ (u_w m)' \text{ was the corrected value of } (u_w m), \text{ and}, \]

\[ p_0 = 101325 \text{ Pa}. \]

Once corrected, the precipitable water was computed from;

\[ a_w((u_w m)') = \frac{0.29 (u_w m)'}{(1 + 14.15 (u_w m)')^{0.635} + 0.5925 (u_w m)'} \]  \hspace{1cm} (D.10)

\[ T_a(m) \]

Transmission of irradiance through aerosols was treated by simply
using equation G.11 and substituting a value for \( k \).
\[ T_R(m) = k^m \] (D.11)

\( k \) at 0.95 seemed to be a good figure for seaside areas and places low in aerosols. Under industrial conditions a value of 0.88 was better. The model used a value of 0.91 for Wooster, which was the same as the value used by Arnfield for Columbus.

**Solar diffuse irradiance**

Diffuse irradiance is made up of components from Rayleigh scattering, scattering from aerosols and backscatterance.

The equation is shown in D.12

\[ D = D_R + D_A + D_S \] (D.12)

where:

\[ D_R = \frac{K_{EX} T_0(u_0 m) [1 - T_R(m)] T_a(m)}{2} \] (D.13)

\[ D_A = K_{EX} [T_0(u_0 m) T_R(m) \cdot a_w(u_w m)] [1 - T_a(m)] w_0 B_a \] (D.14)

and,

\[ D_S = (S + D_R + D_A) (\alpha_s \cdot \alpha_b + \alpha_s^2 \cdot \alpha_b^2 + \ldots) \] (D.15)

where

\( w_0 \) was the single-scattering albedo, and

\[ w_0 = \frac{\text{amount scattered by aerosol}}{\text{total amount attenuated by aerosol}} \] (D.16)
$w_0$ had a value of unity in the model, i.e., all was scattered;

and $B_a$ was the amount scattered downwards by aerosols and which
evidence suggested has a value of 0.85 according to Arnfield, and

where

\[ \alpha_s \] was the albedo of the earth's surface, and

\[ \alpha_b \] was the albedo of the atmosphere.

The infinite series was taken into account by dividing by \(1 - \alpha_s \alpha_b\),
giving

\[
D_S = \frac{(S + D_R + D_A) \, \alpha_s \, \alpha_b}{1 - \alpha_s \, \alpha_b} \tag{D.17}
\]

Total irradiance

Total irradiance $K_{\downarrow}$ was the sum of the direct and the diffuse
irradiance,

\[
K_{\downarrow} = S + D \tag{D.18}
\]
Evapotranspiration

It was important that the water requirement of the plant was established as the water used by the plant was, essentially, a medium for the transportation of nutrients. A number of methods could be used for this; open pan evaporation or lysimeters, but they are conceptually historical in nature. The water is applied once a certain deficit has been reached. In order to ensure that the plant had the relevant nutrients in the leaves, stem, flower and/or fruit, the water and nutrients had to be applied before a deficit was reached. The problem was how to compute the anticipated evapotranspiration of the plant. Fortunately, physicists, plant physiologists and geographers have been diligent in this area: The model that has resulted from such work is commonly called the combination model. This model is a combination of the aerodynamic and the energy budget estimates of evaporation.

Water vapor gradient

Transpiration flux driven by vapor gradient can be likened to Ohm's law. A flux (current) is brought about by the action of a potential difference across a resistance. The potential difference is the difference in water vapor pressure between the stomata of the leaf and the atmosphere at some distance from the leaf. The resistance is the resistance of the system to water
vapor movement, also referred to as the diffusivity, effectively the reciprocal of resistance. Turbulence lowers the resistance, so on a windy day, evapotranspiration increases.

Energy

The water in the plant is in liquid form and so must absorb energy as latent heat to become vapor. Thus the transpiration flux was also driven by a heat flux input.

**The combination model**

The generalized combination model for evaporation was (Arnfield)

\[
Q_E = \frac{\delta S}{\delta S + \gamma} (Q^* - Q_g) \cdot \frac{\rho \cdot Cp \cdot \Delta D}{\tau_a} \quad (E.1)
\]

where;

- \(Q_E\) = energy absorbed by evaporation
- \(\delta S\) = slope of the saturation vapor pressure curve
- \(\gamma\) = psychrometric constant
- \(Q^*\) = incoming energy
- \(Q_g\) = outgoing energy
- \(\rho\) = density of dry air
- \(Cp\) = specific heat of dry air
\[ \Delta D = \text{difference in wet bulb depression between surface and upper level, and} \]

\[ r_a = \text{resistance to water vapor transport.} \]

Stanghellini (1981b) used a combination model for potential evapotranspiration. This model related the evapotranspiration of a well watered, fully developed crop to the net available energy and to vapor pressure deficit, coupled with some diffusion resistance. Stanghellini showed that this model followed the observed evapotranspiration for tomatoes growing in 1977 in Naaldwijk, Holland, from January to July. Statistics for the experiment are shown in Table E.1. The model was remarkably accurate at predicting the potential evapotranspiration of the crop, and further results are shown in Stanghellini (1981a).

<table>
<thead>
<tr>
<th>Table E.1 Statistics on actual vs. calculated values from Stanghellini.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>transpiration</td>
</tr>
<tr>
<td>evapotranspiration</td>
</tr>
</tbody>
</table>
The model used by Stanghellini and incorporated into this model to compute evapotranspiration was as follows:

\[ E_o = \frac{\delta S}{\delta S + \gamma} \cdot \frac{Rn - G}{\lambda} + \frac{\gamma}{\delta S + \gamma} \cdot \frac{\epsilon \cdot \rho \cdot (es - ea)}{\rho_a} \]  (8.2)

where,

- **\( E_o \)** = potential evapotranspiration (mm.s\(^{-1}\))
- **\( \delta S \)** = slope of the saturation vapor pressure curve at air temperature
- **\( \gamma \)** = psychrometric constant (\(= 0.66 \text{ mb.K}^{-1}\))
- **\( Rn \)** = irradiance at earth's surface (W.m\(^{-2}\))
- **\( G \)** = Heat flux into the soil (W.m\(^{-2}\))
- **\( \lambda \)** = latent heat of vaporization of water (J.Kg\(^{-1}\))
- **\( \epsilon \)** = ratio of molecular weight of water vapor to dry air (0.6216)
- **\( \rho \)** = density of air (Kg.m\(^{-3}\))
- **\( \rho_a \)** = air pressure (mb).
- **\( es \)** = saturation vapor pressure at air temperature (mb)
- **\( ea \)** = prevailing vapor pressure of air (mb)
\( r_a \) = resistance to water vapor transport outside the evaporating crop surface (s.m\(^{-1}\))

\( e_a \) could be calculated from

\[
  e_a = \frac{p_a \cdot q}{q + 0.622} \quad \text{(E.3)}
\]

or,

\[
  e_a = \frac{e_s \cdot (\text{relative humidity})}{q + 0.622} \quad \text{(E.4)}
\]

or,

\[
  e_a = \frac{e_s - \gamma(t_a - t_w)}{q + 0.622} \quad \text{(E.5)}
\]

where

\( q \) = humidity ratio

\( t_a \) = dry bulb temperature (°C)

\( t_w \) = wet bulb temperature (°C).

\( r_a \) in the model was given a value of 36sm\(^{-1}\) from Oke, p107. It was an extremely complex variable as is noted by Stanghellini. Her treatise on the subject showed that for short time-span, real time control, it really needed to be understood. Further research in this area is necessary. Provision was made in the program to incorporate modifications to the derivation of \( r_a \) as results of further research become available.
Figure E.1 shows the partitioning of the solar irradiance as it passed into and through the greenhouse and crop canopy as it was used in the model.

Figure E.1. Irradiance transmissions and reflections in the greenhouse and crop canopies.
Incoming solar irradiance (radiation attenuation factor * K↓) was attenuated by the greenhouse cover and the structure of the greenhouse. Transmissivity of the cover and the structure was between 0.50 and 0.70. A figure of 0.60 has been used for the model.

A portion of the irradiance was absorbed by the floor of the greenhouse. Stanghellini used a canopy reflectivity of 0.23 for a fully developed crop and a heat flux into the soil of 0.05 of the net radiation available at the top of the canopy. A highly reflective white polyethylene ground cover was used in the greenhouses at OARDC. This served two purposes. The first was to reflect light falling onto the ground back into the canopy of the crop, increasing the absorptivity of the crop, and the second was to reduce the evaporation of water from the surface of the soil, reducing the necessary heat input to the greenhouse. Of the five percent of the net radiation at the top of the crop cover reaching the floor, 0.8 of that was assumed reflected back into the crop where it was all absorbed.

Radiation absorbed by the crop was calculated as follows:

\[
I_{\text{crop}} = Rn - G \quad \text{(E.6)}
\]

\[
= T_F \cdot K↓ \cdot (0.60)(0.77)(0.95 + 0.05\cdot(0.80)) \quad \text{(E.7)}
\]

where \( T_F \) was the transmission factor from the probability curve at the mode.

\[
T_F = \frac{a - 1}{a + b - 2} \quad \text{(E.8)}
\]
where $a$ and $b$ were from the $\beta$ distribution.

The evaporation of water from the soil was taken to be zero as the greenhouse modeled had a white polyethylene cover on the floor which reduced evaporation from the floor to negligible proportions. The plants were placed on rockwool growing medium with small holes cut in the surface of the enclosing plastic bag of the medium to allow the roots of the plant to penetrate into the rockwool. As a result, all water passing into the atmosphere of the greenhouse came from the plant transpiration as almost no growth medium was exposed to the atmosphere.

As solar radiation increased, temperature ($t_a$), relative humidity ($f(t_a, t_b)$), air density ($\rho$), saturation vapor pressure ($e_s$), saturation vapor pressure slope ($\delta S$), and the latent heat of water ($\lambda$) changed. The slope of the saturation vapor pressure curve, $\delta S$, varies from 1.447 at 20°C to 2.434 at 30°C. This was a significant change and had to be considered when dealing with a situation with varying temperatures. Table E.2 shows the relationships of these items to temperature in the relevant range.
Table E.2 Parameter relationships to air temperature

<table>
<thead>
<tr>
<th>Temperature ta °C</th>
<th>Density of dry air (at 1012mb) ρ kg.m⁻³</th>
<th>Saturation Vapor Press. es mb.</th>
<th>Approx. svp slope δS</th>
<th>Latent heat of Vaporization λ J.kg⁻¹x10⁶</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1.245</td>
<td>12.28</td>
<td>0.822</td>
<td>2.479</td>
</tr>
<tr>
<td>15</td>
<td>1.224</td>
<td>17.05</td>
<td>1.097</td>
<td>2.467</td>
</tr>
<tr>
<td>20</td>
<td>1.203</td>
<td>23.38</td>
<td>1.447</td>
<td>2.455</td>
</tr>
<tr>
<td>25</td>
<td>1.183</td>
<td>31.67</td>
<td>1.887</td>
<td>2.443</td>
</tr>
<tr>
<td>30</td>
<td>1.163</td>
<td>42.42</td>
<td>2.434</td>
<td>2.431</td>
</tr>
<tr>
<td>35</td>
<td>1.144</td>
<td>56.22</td>
<td>3.108</td>
<td>2.419</td>
</tr>
</tbody>
</table>

These figures were computed from the equations given in the ASAE Standards 1984.

The potential evapotranspiration computed by the model was most sensitive to the difference between the saturation vapor pressure and the prevailing vapor pressure of air, es-ea, and the slope of the saturation vapor pressure curve, δS. Saturation vapor pressure changes considerably with temperature as shown in Table E.2. Internal temperature of a greenhouse in Ohio in the winter could vary from a low of 16°C to a high of 30°C within the period of one day. Therefore the slope of the saturation vapor pressure curve, δS, could not be assumed constant as was done by Soribe (1972).

The prevailing vapor pressure of the air, ea, was derived from wet bulb depression, a subtraction of two temperatures which added errors of
measurement. Thus accurate measurement of both dry bulb and wet bulb temperatures cannot be over-emphasized.

An interesting aside was that atmospheric pressure was not measured in the greenhouse weather station and yet it was required for accurate evapotranspiration calculations.
APPENDIX F

CROP NUTRITION RULEBASE

Discussion

The rulebase includes the questions and legal values that were acceptable to the inference software. It was deemed better to define the possible answers and give the operator a choice of answers. This circumvented the problem of mis-spelling of words and parsing of sentences.

The rulebase

question(growth)=Which of the following best describes the plant growth?
legalvals(growth)=stunted, normal, elongated

question(leaf_color)=If leaves are affected, which of the following best describes the color?
legalvals(leaf_color)=normal_green, yellow/green, fading_to_brown, bronzed, dark_green, pale_green_to_yellow

question(leaf_margins)=What is the color of the leaf margins?
legalvals(leaf_margins)=normal_green, yellow/green

question(problem_location)=Where on the plant is the problem located?
legalvals(problem_location)=older_leaves, younger_leaves, uniform

question(flower_size)=What is the size of the flowers on the plant?
legalvals(flower_size)=none, small, normal, large
question(leaf_size)=What is the size of the upper leaves?
legalvals(leaf_size)=small, normal, large

question(internode_length)=What is the internode length of the younger nodes of the plant?
legalvals(internode_length)=short, normal, long

question(chlorosis)=Is there chlorosis present in the leaves?
legalvals(chlorosis)=yes, no, blotchy

question(chlorosis_flow)=Is there any movement of any chlorosis present?
legalvals(chlorosis_flow)=no_movement, leaf_edge_inwards

question(leaf_characteristics)=What are the characteristics of the leaves?
legalvals(leaf_characteristics)=normal, stiff, wilting, dessicated

question(problem_flow)=What is the flow direction of the problem?
legalvals(problem_flow)=older_to_younger_leaves, younger_to_older_leaves

question(apical_meristem)=How does the apical meristem of the plant look?
legalvals(apical_meristem)=normal, dead

question(leaf_shape)=What is the shape of the leaves?
legalvals(leaf_shape)=normal, curved, cupped_upwards, cupped_downwards

question(leaf_appearance)=What is the appearance of the leaf surface?
legalvals(leaf_appearance)=normal, brown_veins, fine_interveinal_mottling, coarse_interveinal_mottling

question(necrosis)=Are there any necrotic areas on the leaves?
legalvals(necrosis)=none, slight, between_the_veins, leaf_edges
question(leaf_burn)=Is there leaf burn on any of the leaves?
legalvals(leaf_burn)=yes, no

question(new_leaf_size)=What is the size of new leaves?
legalvals(new_leaf_size)=normal, small

rule1: if
growth=stunted and
leaf_color=yellow/green and
problem_location=older_leaves and
flower_size=large and
leaf_nitrate=not_known
then
nutrition=deficiency_in_nitrogen.

rule2: if
growth=stunted and
leaf_color=dark_green and
leaf_burn=yes and
problem_location=older_leaves and
leaf_shape=curved and
leaf_nitrate=not_known
then
nutrition=surplus_of_nitrogen.

question(leaf_nitrate)=What is the nitrate-nitrogen present in dry leaf analysis?
legalvals(leaf_nitrate)=not_known, less_than_0.1%, from_0.1_%_to_0.3%, more_than_0.3%

rule3: if
leaf_nitrate=less_than_0.1%
then
nutrition=deficiency_in_nitrogen.
rule4: if
leaf_nitrate=more_than_0.3%
then
nutrition=surplus_of_nitrogen.

rule5: if
growth=stunted and
leaf_color=fading_to_brown and
leaf_phosphorus=not_known
then
nutrition=deficiency_in_phosphorus.

question(leaf_phosphorus)=What is the phosphate present in dry leaf analysis?

legalvals(leaf_phosphorus)=not_known, less_than_0.8%, more_than_0.8%

rule7: if
leaf_phosphorus=less_than_0.8%
then
nutrition=deficiency_in_phosphorus.

rule9: if
growth=stunted and
internode_length=short and
leaf_size=small and
leaf_color=bronzed and
leaf_margins=yellow/green and
leaf_potassium=not_known
then
nutrition=deficiency_in_potassium.
question(leaf_potassium) = What is the potassium present in dry leaf analysis?
legalvals(leaf_potassium) = not_known, less_than_3%, more_than_3%

rule11: if
leaf_potassium = less_than_3%
then
nutrition = deficiency_in_potassium.

rule13: if
chlorosis = yes and
chlorosis_flow = leaf_edge_inwards and
problem_flow = older_to_younger_leaves and
leaf_magnesium = not_known
then
nutrition = deficiency_in_magnesium.

question(leaf_magnesium) = What is the magnesium present in dry leaf analysis?
legalvals(leaf_magnesium) = not_known, less_than_0.5%, more_than_0.5%

rule15: if
leaf_magnesium = less_than_0.5%
then
nutrition = deficiency_in_magnesium.

rule17: if
chlorosis = yes and
chlorosis_flow = no_movement and
growth = stunted and
internode_length = short and
problem_location = younger_leaves and
leaf calcium=not known
then
nutrition=deficiency_in_cacium.

question(leaf calcium)=What is the calcium present in dry leaf analysis?
legalvals(leaf calcium)=not_known, less_than_6%, more_than_6%

rule19: if
leaf calcium=less_than_6%
then
nutrition=deficiency_in_cacium.

rule21: if
growth=stunted and
leaf size=small and
leaf color=pale_green_to_yellow and
problem location=younger leaves and
leaf sulphur=not known
then
nutrition=deficiency_in_sulphur.

question(leaf sulphur)=What is the sulphur present in dry leaf analysis?
legalvals(leaf sulphur)=not_known, less_than_0.6%,
more_than_0.6%

rule23: if
leaf sulphur=less_than_0.6%
then
nutrition=deficiency_in_sulphur.

rule25: if
apical meristem=dead and
leaf_shape=cupped_upwards and
leaf_characteristics=stiff and
leaf_boron=not_known
then
nutrition=deficiency_in_boron.

rule26: if
leaf_margins=yellow/green and
problem_location=older_leaves and
leaf_shape=cupped_downwards and
leaf_characteristics=wilting and
problem_flow=older_to_younger_leaves and
growth=stunted and
leaf_size=small and
leaf_boron=not_known
then
nutrition=surplus_of_boron.

question(leaf_boron)=What is the boron present in dry leaf analysis?
legalvals(leaf_boron)=not_known, less_than_40ppm,
from_40ppm_to_300ppm, more_than_300ppm

rule27: if
leaf_boron=less_than_40ppm
then
nutrition=deficiency_in_boron.

rule28: if
leaf_boron=more_than_300ppm
then
nutrition=surplus_of_boron.

rule29: if
growth=stunted and
internode_length=short and
leaf_size=small and
chlorosis=blotchy and
leaf_copper=not_known
then
nutrition=deficiency_in_copper.

question(leaf_copper)=What is the copper present in dry leaf
analysis?
legalvals(leaf_copper)=not_known, less_than_7ppm,
more_than_7ppm

rule31: if
leaf_copper=less_than_7ppm
then
nutrition=deficiency_in_copper.

rule33: if
leaf_appearance=fine_interveinal_mottling and
problem_location=younger_leaves and
necrosis=between_the_veins and
growth=stunted and
new_leaf_size=small and
leaf_manganese=not_known
then
nutrition=deficiency_in_manganese.

rule34: if
leaf_appearance=brown_veins and
problem_location=older_leaves and
necrosis=between_the_veins and
problem_flow=older_to_younger_leaves and
leaf_manganese=not_known
then
nutrition = surplus_of_manganese.

question(leaf_manganese) = What is the manganese present in dry leaf analysis?
legalvals(leaf_manganese) = not_known, less_than_100ppm, from_100ppm_to_500ppm, more_than_500ppm

rule35: if leaf_manganese = less_than_100ppm then nutrition = deficiency_in_manganese.

rule36: if leaf_manganese = more_than_500ppm then nutrition = surplus_of_manganese.

rule37: if leaf_color = pale_green_to_yellow and problem_location = older_leaves and problem_flow = older_to_younger_leaves and flower_size = small and leaf_molybdenum = not_known then nutrition = deficiency_in_molybdenum.

question(leaf_molybdenum) = What is the molybdenum present in dry leaf analysis?
legalvals(leaf_molybdenum) = not_known, less_than_0.8ppm, more_than_0.8ppm

rule39: if leaf_molybdenum = less_than_0.8ppm then
nutrition=deficiency_in_molybdenum.

rule41: if leaf_appearance=fine_interveinal_mottling and problem_location=younger_leaves and necrosis=leaf_edges and problem_flow=younger_to_older_leaves and leaf_iron=not_known then
nutrition=deficiency_in_iron.

question(leaf_iron)=What is the iron present in dry leaf analysis? legalvals(leaf_iron)=not_known, less_than_100ppm, more_than_100ppm

rule43: if leaf_iron=less_than_100ppm then nutrition=deficiency_in_iron.

rule45: if leaf_appearance=coarse_interveinal_mottling and problem_location=older_leaves and necrosis=slight and internode_length=short and problem_flow=older_to_younger_leaves and leaf_zinc=not_known then nutrition=deficiency_in_zinc.

question(leaf_zinc)=What is the zinc present in dry leaf analysis? legalvals(leaf_zinc)=not_known, less_than_100ppm, from_100ppm_to_900ppm, more_than_900ppm
rule47: if  
leaf_zinc=less_than_100ppm  
then  
nutrition=deficiency_in_zinc.

rule48: if  
leaf_zinc=more_than_900ppm  
then  
nutrition=surplus_of_zinc.

question(crop_height)=What is the height of the plant?  
legalvals(crop_height)=less_than_four_feet, more_than_four_feet

question(fruit_presence)=Is there fruit present on the plant?  
legalvals(fruit_presence)=yes, no

question(picking)=Have you started picking fruit from the crop?  
legalvals(picking)=yes, no

question(flower_presence)=Is there an abundance of flowers present on the crop?  
legalvals(flower_presence)=yes, no

rule50: if  
crop_height=less_than_four_feet and  
flower_presence=no  
then  
physage=plant_to_flower.

rule51: if  
crop_height=more_than_four_feet and  
picking=no and  
flower_presence=no  
then  
physage=plant_to_flower.

rule52: if  

fruit_presence=yes and picking=yes
then physage=fruiting)

rule53: if flower_presence=yes and fruit_presence=yes and picking=no then
physage=flower_to_fruit.

question(recipe)=What is the recipe number? legalvals(recipe)=1, 2, 3, 4, 5, 6, 7, 8, 9

rule101: if physage=plant_to_flower and recipe=1 then
nitrogen=75_to_120_mg/l and potassium=150_to_240_mg/l and calcium=80_to_120_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=50_to_40_mg/l and MaxEC=1800_micromhos.

rule102: if physage=plant_to_flower and recipe=2 then
nitrogen=75_to_120_mg/l and potassium=150_to_240_mg/l and calcium=120_to_160_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=1800_micromhos.

rule103: if
physage=plant_to_flower and
recipe=3
then
nitrogen=75_to_120_mg/l and
potassium=150_to_240_mg/l and
calcium=160_to_200_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=1800_micromhos.

rule104 if
physage=plant_to_flower and
recipe=4
then
nitrogen=120_to_160_mg/l and
potassium=240_to_320_mg/l and
calcium=80_to_120_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=1800_micromhos.

rule105: if
physage=plant_to_flower and
recipe=5
then
nitrogen=120_to_160_mg/l and
potassium=240_to_320_mg/l and calcium=120_to_160_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=1800_micromhos.

rule106:  if physage=plant_to_flower and recipe=6 then nitrogen=120_to_160_mg/l and potassium=240_to_320_mg/l and calcium=160_to_200_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=1800_micromhos.

rule107:  if physage=plant_to_flower and recipe=7 then nitrogen=160_to_200_mg/l and potassium=320_to_400_mg/l and calcium=80_to_120_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=1800_micromhos.

rule108:  if physage=plant_to_flower and recipe=8
then
nitrogen=160_to_200_mg/l and
potassium=320_to_400_mg/l and
calcium=120_to_160_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=1800_micromhos.

rule109: if
physage=plant_to_flower and
recipe=9
then
nitrogen=160_to_200_mg/l and
potassium=320_to_400_mg/l and
calcium=160_to_200_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=1800_micromhos.

rule111: if
physage=flower_to_fruit and
recipe=1
then
nitrogen=150_to_200_mg/l and
potassium=300_to_400_mg/l and
calcium=60_to_140_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=2500_micromhos.

rule112: if
physage=flower_to_fruit and recipe=2
then
nitrogen=150_to_200_mg/l and potassium=300_to_400_mg/l and calcium=140_to_220_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2560_micromhos.

rule113: if physage=flower_to_fruit and recipe=3
then
nitrogen=150_to_200_mg/l and potassium=300_to_400_mg/l and calcium=220_to_300_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule114: if physage=flower_to_fruit and recipe=4
then
nitrogen=200_to_250_mg/l and potassium=400_to_500_mg/l and calcium=60_to_140_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.
rule115: if
physage=flower_to_fruit and
recipe=5
then
nitrogen=200_to_250_mg/l and
potassium=400_to_500_mg/l and
calcium=140_to_220_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=2500_micromhos.

rule116: if
physage=flower_to_fruit and
recipe=6
then
nitrogen=200_to_250_mg/l and
potassium=400_to_500_mg/l and
calcium=220_to_300_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=2500_micromhos.

rule117: if
physage=flower_to_fruit and
recipe=7
then
nitrogen=250_to_300_mg/l and
potassium=500_to_600_mg/l and
calcium=60_to_140_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule118: if physage=flower_to_fruit and recipe=8 then nitrogen=250_to_300_mg/l and potassium=500_to_600_mg/l and calcium=140_to_220_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule119: if physage=flower_to_fruit and recipe=9 then nitrogen=250_to_300_mg/l and potassium=500_to_600_mg/l and calcium=220_to_300_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule121: if physage=fruiting and recipe=1 then nitrogen=50_to_100_mg/l and potassium=100_to_200_mg/l and calcium=80_to_150_mg/l and
phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule122: if physage=fruiting and recipe=2 then
          nitrogen=50_to_100_mg/l and potassium=100_to_200_mg/l and calcium=150_to_230_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule123: if physage=fruiting and recipe=3 then
          nitrogen=50_to_100_mg/l and potassium=100_to_200_mg/l and calcium=230_to_300_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule124: if physage=fruiting and recipe=4 then
          nitrogen=100_to_150_mg/l and
potassium=200_to_300_mg/l and calcium=80_to_150_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule125: if physage=fruiting and recipe=5 then
nitrogen=100_to_150_mg/l and potassium=200_to_300_mg/l and calcium=150_to_230_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule126: if physage=fruiting and recipe=6 then
nitrogen=100_to_150_mg/l and potassium=200_to_300_mg/l and calcium=230_to_300_mg/l and phosphorus=40_to_75_mg/l and magnesium=30_to_50_mg/l and sulphur=30_to_40_mg/l and MaxEC=2500_micromhos.

rule127: if physage=fruiting and recipe=7
then
nitrogen=150_to_200_mg/l and
potassium=300_to_400_mg/l and
calcium=80_to_150_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=2500_micromhos.

rule128: if
physage=fruiting and
recipe=8
then
nitrogen=150_to_200_mg/l and
potassium=300_to_400_mg/l and
calcium=150_to_230_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=2500_micromhos.

rule129: if
physage=fruiting and
recipe=9
then
nitrogen=150_to_200_mg/l and
potassium=300_to_400_mg/l and
calcium=230_to_300_mg/l and
phosphorus=40_to_75_mg/l and
magnesium=30_to_50_mg/l and
sulphur=30_to_40_mg/l and
MaxEC=2500_micromhos.
APPENDIX G

GLOSSARY OF TERMS

Bayes' Rule: The probability rule which relates probabilities of outcomes and allows the assessment of \( p(q_1 | R) \) from the quantities \( p(q_1), p(q_2), p(R | q_1) \) and \( p(R | q_2) \) by use of the following equation, commonly termed Bayes' Rule:

\[
p(q_1 | R) = \frac{p(R | q_1) p(q_1)}{p(R | q_1) p(q_1) + p(R | q_2) p(q_2)}
\]

Certainty factor: The measure of likelihood of a circumstance used in the software Personal Consultant Plus, by Texas Instruments.

Chance Node: The position in a decision tree indicating a future event. Branches from the chance node show the chances of situations occurring in the future.

'Comax': An expert system to advise cotton farmers.

Crop: A product of an agricultural endeavor.

Decision Analysis: The science of decision analysis using decision trees, probability and utility to aid decision makers.

Decision Node: A position in the decision tree that shows the point at which certain decisions have to be made.

Decision options: The options open for selection at a decision node in a decision tree.

Decision tree: A graphical representation of the decision process.
**Expert:** A person who can give advice on what to do in certain situations, such advice usually being based upon heuristic knowledge and computational procedures.

**Fuzzy sets:** Sets that cannot be defined precisely, that is, they have some areas that are unknown.

**Generic tree:** A predetermined decision tree used to analyze different, but similar, scenarios.

**Inference engine:** A computer program that manipulates rules of an expert system in an attempt to find answers to a question.

**Infestation:** The accumulation of unwanted pests in a crop.

**Nutrients:** The food for plants carried in the irrigation water.

**Nutrient recipes:** Various combinations of nutrients.

**Options:** A list of decisions that could be made at this point in time, given the present physical situation.

**Outcome:** The result of following a certain path through all of its decision nodes and chance nodes to a conclusion.

**Path:** A series of connections on a decision tree joining decision nodes to chance nodes which lead from the present decision being made to an outcome on the decision tree.

**Probabilities:** The measure of an person's belief in a proposition, given the evidence available to the person at the time.

**'PROSPECTOR':** An Expert system that identifies likely locations of mineral resources given results from drillings.
Irradiance transmission factor: The ratio between the radiation received at a point on the earth's surface and the calculated clear sky radiation for that point at that time.

Rule: A statement in an expert system that is in the form of an "IF . . . THEN . . . " statement.

Utility: A number giving the desirability of an outcome.

Utility function: A mathematical function that relates utility to outcomes.