Modelling for Decision Support in the Vegetable and Fruit Supply Chain

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Abstract
Quality modelling in agri-supply chains has become increasingly popular in R&D environments, because of the availability of large amounts of experimental data and mathematical models. At the same time, in industrial supply chains a strong need exists for support in making complex decisions with respect to logistic, commercial, technical, financial and other aspects. Nevertheless, the majority of research models is not being used in real world applications. Our claim is that a more explicit analysis of specific decision-making processes will help to construct models that will be of use in practice. Therefore we propose to pay special attention to this aspect of the modelling process and to separate it from behavioural modelling. We distinguish between decision and control variables on one hand and behavioural variables on the other. Common modelling practice only deals with the latter. We review three cases from our own project experience with this conceptual distinction in mind: fresh-cut vegetables in MA-packaging, ripeness of mangoes and optimal planning of sowing and harvesting. This analysis has resulted in a systematic procedure to analyse the decision-making process and to construct context relevant models. Careful examination of potential applications along these lines will improve the interaction between users and developers of product and process models.

INTRODUCTION
In agricultural research environments increasing effort is spent on building computational models. These models predict quality behaviour of fresh products or compute other supply chain variables. The objective is to assist in optimising agricultural supply chain efficiency and consumer appreciation. However, the actual utilisation of these models in practical decision making still does live up to its expectations. This cannot be imputed simply to their limited correspondence with real processes, as is often suggested by product experts or supply chain managers. As a matter of fact, any model will fail to comply with experimental observations at some point. A much more important factor for the relatively unsuccessful application of models is the fact that no explicit statement is made about the problem context in which they are to be applied. A lot of work is devoted to statistical and physiological details of a model; too little attention is given to describing how it can be used in practice. This paper reviews a number of previous projects to see how this link could actually be made.

To motivate our approach we first observe that the ultimate use of models in general is to support decision-making. Ideally, the model tells us whether a certain action is worth to be taken, possibly in combination with a level of utility\textsuperscript{1}. That means that in principle we need a single decision variable that has a certain value. Often this variable is referred to as quality, which, actually, only expresses the fact that a net appreciation value exists within a certain decision-making process. Explicit description of the underlying decision-making process is required to give an unambiguous meaning to the quality

\textsuperscript{1}In the area of decision support systems (DSS) it is common to define a so-called utility function to express the value of a specific solution [Klein et al.,1995].
notion used in a specific problem context. This, in turn, determines the underlying assumptions that are needed to construct an adequate model.

For example, in the supply chain of fresh-cut vegetables a logistic manager may have to decide whether to invest in new cooling equipment. A high-level decision variable could be ‘the increase of market share for fresh-cut vegetables in the next year in the Netherlands’. A model is required that predicts market share changes due to new cooling equipment sufficiently accurately. However, the underlying model will depend on many assumptions about technical, commercial, organisational and other aspects. Too many different disciplines and information sources would have to be consulted and linked. The manager could narrow down the decision-making variable to, for example, ‘decrease of product loss in one year’. This means, of course, that he is now focussing on rather technical aspects of product quality and supply chain conditions, taking all other financial, commercial and organisational arguments for granted. For the latter he relies on his own private experience. Now constructing a meaningful model is more feasible because it introduces less complexity and will have solid experimental and theoretical grounds.

Decision-making is mostly a matter of dealing with incomplete and uncertain information. Dividing the overall decision into smaller sub-decisions with their specific constraints and assumptions is a proven method to improve the reliability and transparency of the underlying reasoning.

In this paper we argue that it is useful to carefully define decision-making variables, and to distinguish them from behavioural variables. The reason to do so is twofold. First, by careful construction of a decision variable the underlying assumptions (in practice mostly based on common sense and experience) will be made explicit and tractable. This will either increase the feasibility of building meaningful models or point towards missing information. Second, by separating the decision model from the behavioural model we allow models at each of these levels to be reused. We will further elaborate these two different levels in Section 2. In Section 3 we apply the approach to a number of cases from our own project experience. In Section 4 we describe a step-wise method to construct models that are explicitly related to the decision-making process. Finally, in Section 5 we conclude with an outlook on the expected follow-up of this work.

SEPARATING DECISION MAKING FROM BEHAVIOUR MODELLING

The notion of product quality is frequently used as an output variable in product behaviour modelling. The decision-making context of this variable is usually not well defined. More specific, but still open to multiple interpretations, are quality parameters such as shelf life, product loss, microbial spoilage, sensory quality, overall energy consumption, overall production costs, etc. As a first example consider the widespread notion of product shelf life. It is normally assumed to indicate the time remaining for a product until it will be rejected. It is directly related to product behaviour in terms of microbial growth, texture changes, colouring, etc. On the other hand, this term by itself refers to a decision-making process, viz., ‘under which conditions will the product be rejected?’ By whom and based on which criteria? For the supply chain manager, product shelf life as a decision variable would, for example, be used to decide

- ‘whether the temperature in the supply chain is sufficiently low and stable to leave at least five days at the consumer’,
- ‘whether an appropriate preservative has been employed to reduce product loss in the supply chain’.

In those cases, more appropriate decision variables would respectively have been defined as:

- ‘the maximum amount of time between point of sales and indicated keeping time for average storage conditions at the consumer’ and
- ‘the average time between leaving production and rejection, given standard maximum levels for microbial count, condensation, etc. and standard supply chain conditions’.
These detailed specifications of two interpretations of shelf life require different underlying models and assumptions. As a consequence, they may require different experimental set-ups to calibrate and validate these models.

Although the above argumentation may seem to be playing with details, we claim that a more careful definition of decision variables will help to specify the relation to proper behavioural models. In fact we propose two distinguish two modelling levels as shown in Figure 1. The problem context defines decision variables that are specific and very much application dependent. The decision model links these variables to behavioural variables that express more or less problem independent variables and parameters, including thermodynamics, fluid dynamics, microbial growth, physiological kinetics, biophysical changes, etc. In literature the behavioural variables are often referred to as *objective* variables, to indicate that they are defined and measured independently of individual judgement. However, we want to emphasise that it is not so much a matter of differentiating between observers but rather between different contexts and situations. For example, sweetness is a subjective variable in terms of individual perception, but also depends on the instantaneous situation of the individual (for example the order of consumption).

A second reason for separating decision and behaviour levels is to promote reuse of models at both levels. The behavioural (sub-)models that describe physical, chemical, microbiological and other interactions are more or less context independent. The decision models are task-specific, and therefore are less fit for reuse. It is, however, conceivable to define more or less generic decision tasks, which may suggest natural decision variables and problem solving methods (such as linear programming). In knowledge engineering the separation between the *task* level and the *domain* level is fairly common [Schreiber et al., 2000].

A few additional remarks should be made about the distinction between decision variables and behavioural variables. First we note that sometimes the relation between these two types of variables is chosen to be rather trivial. This happens if a decision is more or less situation independent, for example ‘microbial spoilage = spoilage organism count’. Here it is assumed that the individual and instantaneous perception of ‘spoilage’ is represented by the measurable quantity ‘spoilage organism count’.

Secondly, it is sometimes tempting to select a number of variables to collectively represent a decision variable. A typical example would be ‘sensory quality and microbial spoilage’. However, such a combined variable will still be evaluated as a single value in order to act as a decision variable. Therefore, some kind of utility function will have to be defined that combines the two parts, either by using weighting factors, threshold values or any other algorithm. For purpose of clarity it could also be useful to assign a new name to the combined variable, such as ‘microbial-sensory acceptability by consumers’.

**APPLICATION TO CASE STUDIES**

Given the ideas presented above, we have analysed three of our previous modelling projects and reframed them. In this section we briefly describe these cases. In the following section this will result in a systematic approach which could be followed in future projects.

**Quality versus microbial count and condensation in vegetable MA packages**

Minimally processed vegetables, packed under modified atmosphere (MA), represent an increasing market. Their image is one of quality and freshness, partly due to the transparent film around the product. However, being processed (cut, washed and dried), the vegetables are more susceptible to several kinds of spoilage: microbial spoilage, dehydration, enzymatic browning, etc.

In a dedicated project the objective was to decrease the quality loss of the fresh-cut vegetables. This variable could be recognised as the main decision variable. An example of a decision could be: ‘Will the quality of the product remain high enough in the envisaged distribution chain?’. We assumed quality $Q$ to be represented by microbial...
spoilage $MS$ and formation of water condensate ‘soup’ $WS$, which could be seen as sub-decision variables:

$$Q = [MS, WS]$$

indicating that these variables were investigated on an individual basis rather than that they are related mathematically. Apparently, no explicit choice had been made on the relative importance of these sub-decision variables. As a control variable temperature $T$ around the product was selected. This also needs some clarification, since in practice this temperature cannot always be controlled in detail.

In the next step, behaviour variables were selected that could be related to the above decision variables. Decision variable microbial spoilage $MS$ was considered to be similar, or ‘equal to’ microbial growth $Y \ [\ln(\text{cfu/ml})]$, which seems quite an obvious choice:

$$MS = Y$$

Nevertheless this introduces already the assumption that only the overall microbial count is relevant.

The formation of water condensate ‘soup’ $WS$, the second decision variable, was assumed to be equal to $n_{w,0} \ [\text{mole}]$, the water condensation on the inner side of the packaging. We thus neglect the fact that for the ‘soup’ to occur water needs to form droplets that slide down the packaging material and form a pool altogether:

$$WS = n_{w,0}$$

Next, it was assumed that the process of condensation of water on the product is negligible, since the product is usually warmer than the packaging material, due to respiration processes. That leaves condensation to take place especially on the inner side of the film, the coldest region on the inside of the packaging.

Microbial growth $Y$ was predicted using the differential equation form of the Baranyi-model [Baranyi et al., 1994]:

$$\frac{dY}{dt} = \frac{-q(t)}{q(t)+1} \mu_{max}(1-e^{\mu_{max}t})$$

$$\frac{dq}{dt} = \mu_{max}q(t)$$

where $Y_{max}$ is the natural logarithm of the maximum amount of microbial spots $[\ln(\text{cfu/ml})]$, $\mu_{max}$ is the maximum specific growth rate of the microbes $[\text{h}^{-1/2}]$, $q$ is a measure for the physiological state of the microbes $[\text{units/cfu}]$. The initial value $q(0)$ determines (indirectly) the duration of the lag phase, as a result of the physiological state of the growth medium.

The influence of temperature on model parameter $\mu_{max}$ is described separately from the growth model, by means of the temperature square root model of Ratkowsky [Ratkowsky et al. 1983]:

$$\sqrt{\mu_{max}} = b(T(t)-T_{min})$$

Here $b$ is a regression coefficient $[\text{K}^{-1} \text{ h}^{-1/2}]$ and $T_{min}$ is the theoretical minimum growing temperature $[\text{K}]$. 

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The behaviour variable water condensation on the inner side of the packaging material depends on a water vapour concentration difference, condensation coefficient \( h_{B,O} \) [m/s] and packaging surface area \( A \) [m²]:

\[
\frac{dh_{B,O}}{dt} = (\rho_{air} - \rho_{mol})_{pack.\ layer} \cdot h_{B,O} \cdot A
\]  

(7)

Condensation coefficient \( h_{B,O} \) depends on the Sherwood number, \( Sh \) [-], the diffusion rate of water vapour in air, \( D_{air} \) [m²/s], and characteristic length \( L \) [m] of the product:

\[
h_{B,O} = \frac{Sh \cdot D_{air}}{L}
\]  

(8)

The Sherwood number strongly depends on air velocity, in an indirect way, via the Reynolds number. This airflow originates from natural convection, which occurs due to temperature differences inside the MA package.

The amount of water condensed could be calculated using a complex thermodynamic-biological model of the product and its packaging. This model includes the following sub-models: heat conduction in the product, the packaging air and the packaging material, product respiration, transpiration and product fermentation, (heat) diffusion through the packaging material and forced (heat) convection through the packaging material [Hertog et al, 1997].

The total model was calibrated for the particular product. Subsequently, typical and ideal chains could be simulated, to check whether the maximum microbial count is reached and to check the formation of condensation due to temperature jumps. In the mean time, from these modelling efforts combined with practical experience the idea had grown that actually only the formation of condensate should be considered as a decision variable. The assumption was that microbial growth only becomes a problem condensate is collected. This increased insight lead us to now focus on a detailed model of the condensation process due to natural convection inside the packaging. So, as the chosen decision variable shifted due to insight gained, a different modelling focus was required.

**Ripeness versus firmness of mangoes**

Mangoes are imported from all over the world, where they are grown under different circumstances, harvested at different levels of maturity and transported under non-ideal conditions. Variation in quality is enormous, such that this type of fruit is only little popular. A customer is not able to detect when the fruit will be ready for consumption. A project objective was to ‘ripen’ batches of mangoes actively and specifically by controlling storing conditions, such that they would be more ready to eat at the time they are offered to the consumer. Here, ripeness \( R \) could be recognised as a decision variable. An example of a decision question could be: ‘Will the product be ripe enough when being consumed?’ \( R \) was assumed to be equal to the firmness, \( F \), of the product:

\[
R = F
\]  

(9)

The firmness of the product, indicated on a 5-point scale, was assumed to be determined by control variable temperature sum \( TS \) [K day] in a sigmoid way:

\[
F = \frac{F_{max}}{1 + e^{(TS - \Delta T)}}
\]  

(10)
$k \, [K^{-1} \, day^{-1}]$ and $\Delta TS \, [K \, day]$ are batch specific and their values were acquired using a case based reasoning technique. The model will calculate the temperature sum that is required to overcome a certain difference between actual and desired firmness.

By defining the decision variable ripeness in a simple but yet detailed way (Eqn. 9), in agreement with the client, misunderstandings were avoided, e.g. with relation to the influence of diseases, which is more difficult to predict, on a batch level, than the average firmness. Also, it appeared that a relatively simple model was sufficient to support the decision-maker.

**Processing costs versus sowing-harvesting scheduling**

Sowing and harvesting of vegetables for the sake of canning is planned carefully over the year, in order to encourage the optimal utilisation of processing lines. The objective of a project concerning this subject was to support the sowing and harvesting planning process by means of an optimisation model, reducing total production costs $TC \, [\text{€}]$. A decision to be made might be formulated as ‘the minimum amount of costs to be made given a certain year production and personnel availability’. Decision variable $TC$ relates to the more specific decision variables sowing and harvesting costs $SHC \, [\text{€}]$, costs of under-utilisation of production lines $UPC \, [\text{€}]$, profits of production surplus $PP \, [\text{€}]$ and costs over-production $CO \, [\text{€}]$:

Minimise $TC = f(SHC, UPC, PP, CO)$ (11)

These variables depend on behaviour variables such as ‘number of cans processed product’ and ‘size of harvested area’ in combination with detailed activity based costs. The variables are under constraint by aspects such as number of production lines and maximum amount of harvested area. The planner controls the input by indicating the required amount of production in a year and specifying these constraints. We will not discuss the entire model here, but refer to the project report [Weert et al., 1996].

By focussing on high-level decision variables, such as costs and budgets here, a detailed behavioural model can be made applicable in real world practice. However, and on the other side, complex relations as the above are hard to calibrate, and it is advisable to keep relations between decision variables, control variables and behaviour variables as simple as possible. The behavioural models can be as complex as necessary in a certain situation, since, in general, they are better founded and more reliable. In fact it appeared that the experienced planner was not so much asking for fully automated optimisation, but rather for a efficient way to check the consequences of alternative planning scenarios. His intuition was needed to take all kinds of day-to-day effects into account. Full automation would not let him do this, and would have resulted in results that were not trustworthy.

**STEP-WISE MODELLING OF DECISION AND BEHAVIOUR VARIABLES**

In the cases above we have observed that clarifying the decisions for which model support is requested helps tracking implicit assumptions and preventing misinterpretation. Careful analysis of who is going to decide on what will help construct a model that will be used in practice. This analysis should be an inherent element of regular modelling practice. Therefore, we will now describe a step-wise process of model construction. This procedure starts from the task performed by an agent (person or computer) somewhere within a particular supply chain.

The approach consists of the following steps:

1. Define the role of the decision-maker. Determine the degrees of freedom (span of control) for this role and determine how much of the decision process will be based on common sense. Analyse the experience and information sources the agent will be using.
2. Determine decision-making interests. Different roles have different interests. For example, a production manager may want to cut energy consumption; a consumer
looks for a tasty product.

3. Select relevant decision variables. This is in general the most difficult step and is often omitted. To reduce complexity, try not to consider the required behavioural model at this moment.

4. Select control variables that the decision-maker will use to manipulate behavioural variables. A typical example in fresh supply chains is temperature.

5. Select behavioural variables and relate them to the previously selected decision and control variables. Even a simple relation can be used (for example ‘equal to’ or ‘inversely proportional to’) provided it is described explicitly.

6. Construct a model that relates the behavioural variables. Use generally available partial models from physics, physiology, etc. where possible. Go to the next step if some models are hard to validate within the given context and communicate this with the decision-maker.

7. Iterate the process if at some point it fails and explicitly archive crucial modelling assumptions and decisions that were made during the process.

The above approach may be a first step to reduce the risk of unused modelling projects and too high expectations from model users. A more formal and detailed description is to be developed, building on general literature on decision support systems. One of the issues is dealing with the costs and benefits of the alternative decisions proposed.

CONCLUSION

In this paper we have argued that in favour of a better exploitation of the large amount of scientific models constructed in R&D environments, one needs to analyse and describe the application context carefully. This application context can best be considered as a decision-making process that determines which control actions are to be executed. To that end we have proposed to distinguish two layers of modelling:

- The decision modelling layer, which describes context specific variables that can be used in actual decision making processes.
- The behavioural modelling layer, which expresses more or less problem independent relations between physical, chemical, microbiological quantities, etc.

Based on our experiences we have developed a systematic modelling approach that builds on these two model layers. This approach will ensure that underlying modelling assumptions will become explicit in an early stage of the project, preventing miscommunications and misunderstandings between industrial stakeholders and researchers. This agreement may either lead to a different decision process or a different underlying behaviour model. Furthermore, revision of previous modelling decisions is enhanced using this approach. The approach may require several iterations, in which either different models are constructed or the decision process is altered. Three cases taken from our own project experience in the vegetable and fruit supply chain have illustrated the proposed method.

We have presented a rather intuitive way to link general product and process models to particular tasks in practice. Our ambition is to further formalise this way of thinking and construct more detailed guidelines and tools to support decision-based modelling of supply chain aspects. Of course the general modelling issue is not restricted to the domain of fresh product supply chains, but in our case that will be the validation and inspiration environment for a more robust method.

Literature Cited


Figures

**Fig. 1.** Two modelling levels: the decision level and the behaviour level.

**Fig. 2.** The decision level and the behaviour level in the particular case of quality modelling of vegetables in MA packages.
Fig. 3. The decision level and the behaviour level in the particular case of quality modelling of mangoes.

Fig. 4. The decision level and the behaviour level in the particular case the modelling of sowing-harvesting scheduling.