Bert van 't Ooster

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Albertus (Bert) van 't Ooster

Thesis committee

Promotor
Prof. Dr E.J. van Henten
Professor of Farm Technology
Wageningen University

Co-promotors
Dr J. Bontsema
Senior scientist
Wageningen UR Greenhouse Horticulture

Dr S. Hemming
Senior scientist and Team leader Greenhouse Technology
Wageningen UR Greenhouse Horticulture

Other members
Prof. Dr L.F.M. Marcelis, Wageningen University
Prof. Dr Y. Edan, Ben Gurion University of the Negev, Beer Sheva, Israel
Prof. Dr W. Saeys, KU Leuven, Belgium
Prof. Dr I.J.B.F. Adan, Eindhoven University of Technology

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Chapter 1

General introduction and outline of the thesis

A. van 't Ooster

1 General introduction

1.1 Background

Dutch greenhouse horticulture is a very successful sector with a high level of technology. The sector, including supply industry and applied research, set an example for many, all over the world (Baltussen & Smit, 2013). However, also Dutch horticulture faces problems of economic nature like small margins, economies of scale, rising costs of resources such as labour, energy, seed, etc., limited availability of sufficiently skilled human labour, high and sometimes risky investments in production systems and technology (Van Henten, 2006; Mulder, Lans, Verstegen, Biemans, Meijer, 2007; Montero, van Henten, Son, Castilla, 2011; Van der Meulen, van Everdingen, Smith, 2012).

In Dutch horticulture, labour is a main cost factor which represents 25-30% of the specific production costs per m^2 greenhouse in cut-flower production (Van der Meulen et al., 2012). Also, not many people have aspirations for jobs in greenhouses because of harsh climate conditions and repetitive work. This raises a challenge for labour organisation and labour management. Shortage of qualified workforce is a real risk in horticultural practice (Aldous, Dixon, Darnell, Pratley, 2014). A strong dependence on labour together with the irregular availability of manpower make effective labour organisation a crucial but challenging success factor for greenhouse horticulture (Bechar & Edan, 2005). In order to train new workers and to allocate unexperienced workers in the various crop operations, the on-floor labour management is an almost full time activity for one or more supervising managers.

The solution direction for labour related problems, high labour costs and low workforce availability, is in general to increase labour productivity by, 1) improving the efficiency of human labour, 2) improving labour management, 3) supporting and/or replacing human labour by technology, or 4) improving job satisfaction. This solution direction exists for a long time already. Labour productivity increase during the last 100 years in agriculture, horticulture, and industry are silent witnesses (Crafts & Toniolo, 1996). Also during the next decades, improving labour efficiency in horticulture will be important to stay competitive on the (inter)national market.

For both growers and for horticultural supply industry it is a challenge to introduce innovations of crop operational processes with clear value for their businesses. Growers feel urgency for innovations in the near future. However, decisions concerning modifications of the production systems or introduction of new technology like vision, robotics, augmented reality etc. are not easily made because growers have to be sure that on the one hand production costs are reduced, while on the other hand production levels and product quality are maintained or improved, to stay in the market. For the supply industry and their designers the challenge is to create the right opportunities for growers. However, they should make sure that the solution realises the intended effect for as many growers as possible. This challenge also holds, but to a lesser extent, for applied scientific research that should provide society with useful research results. To reduce risk and to improve economic strength, both growers and supply industry require means to evaluate strategic decisions with respect to business process re-design. In addition growers require means to evaluate operational decisions in labour management.

Let's elaborate a little further on the challenges growers are currently facing when it comes to improving labour efficiency. As innovators who feel urgency and as early adopters, growers tend to invest in innovations, which are normally more risky than investments in mature technologies (Diederen, Van Meijl, Wolters, Bijak, 2003). Where possible, they operate their company with increasing use of industrial methods (Giacomelli, Castilla, van Henten, Mears, Sase, 2008). A lot has been done to increase labour productivity through adjustments to the production process focussing on effectively doing single, well defined tasks and through introducing new technology that alleviates work, and supports or replaces workers. For example at a nursery for ornamentals, market ready plants are selected and classified by means of computer vision and electronic labelling. Computers collect client orders from a buffer of market ready plants. Manual labour is strongly reduced. Workers mainly transport plant batches between the greenhouse and the processing room. Workers in sweet pepper, another example, have single well defined tasks, like harvesting sweet pepper in an assigned set of paths, their performance is tracked electronically for a performance based salary or even a fee per harvested fruit, and automatic guided vehicles provide for transportation of the labelled product in the main aisle. Similar systems exist in vegetable crops, ornamentals, and cut-flower.

Generally adopted industrial methods in the Netherlands and North Western Europe are: application of internal logistics, product handling like sorting and packing, and to a lesser extent the more general methods business process re-design (Kazuo Nakatani, 1999) and lean manufacturing (Shah & Ward, 2003). However, further improvement of labour efficiency is not easy because innovation processes have arrived at system elements where analogy with industry is partly or fully lost because of the complexity of the crop and its environment, and where, consequently, failure of investment may increase. The system is complex because the crop environment is unstructured and vulnerable, a large variability of crop maintenance operations is needed (Bechar & Edan, 2003; Ota et al., 2007) for many different products with specific characteristics as well as intrinsic product variability.

System innovations can therefore no longer rely on a "quick-and-dirty" assessment of their feasibility as done in, for instance, the Kesselring method (Siers & van den Kroonenberg,

2004) and to a lesser extent also in value engineering (Miles, 1961). Questions on what performance improvement is to be expected and what labour scenario performs best, cannot be answered easily. Should a grower use a static or mobile cultivation system, static or mobile machinery, human-machine interaction or autonomous systems? Though research on intelligent systems for automation of horticultural processes is substantial (Bac, Henten, Hemming, Edan, 2014), system analysis for an effective embedding of this new technology in crop operations, being very relevant, is still not conducted with quantitative models yet.

Despite many successes of implementing automation of processes in greenhouses in the past, also real risks occur, such as underperformance, lagging benefits, partial system failure and, in extreme cases, bankruptcy of entrepreneurs (Montero et al., 2011). Only when design concepts pass a quantitative evaluation, the risk of failure of pioneer investments can be reduced.

Growers require proof that their investment is secure and satisfies their needs. When industry, growers and applied research join forces in collaborative design, supported with quantitative evaluation of design concepts, this proof may be delivered.

1.2 Motivation for modelling operational processes

Successful innovations have to be technologically and economically feasible, have to meet customer requirements and must have a minimised risk of failure. Designers of future crop cultivation systems in greenhouses will need new quantitative methods to assess this feasibility already in the design stage. The proposed methods should include a better systematic and quantitative analysis of the production process, a systematic (re)design of alternatives for a production process or a technological solution, and simulation of these solutions functioning in their planned environment.

Existing systematic design paradigms already provide us with methods to generate design concepts. The methods are characterised by transparency and openness for design iteration, and for involvement of relevant stakeholders (Cross, 2001; Siers & van den Kroonenberg, 2004; Groot Koerkamp & Bos, 2008; Hemming, van Henten, van ’t Ooster, Vanthoor, Bakker, 2008). The evaluation of alternative concepts in systematic design is based on classification of expert expectation of system performance with respect to assessment criteria based on stakeholder requirements. This makes selection of a suitable alternative intuitive, viewpoint dependent and qualitative. It is effective in separating promising solutions from unfavourable solutions, but it is not fit for evaluating feasibility and risks. It has however been shown that this systematic design paradigm already leads to higher performance and less risk of failure especially when combined with risk assessment (Lough, Stone, Tumer, 2009). Quantitative analysis and quantitative evaluation of design concepts contribute to even more quality and reliability of solutions (Kapur, 2014).

Model based evaluation of crop operations in the as-is situation and in several to-be situations as created in the design process enables quantitative comparison of the performance of alternatives with the current situation. This may strongly improve the output quality and lead time of the design process itself. Also, simulation of horticultural production systems offers the opportunity to compare the performance of alternatives under predefined controlled conditions, without the direct need for repeated field experiments, and independently of the growing season (Bechar & Edan, 2005).

It is the ambition of this research to initiate and develop a model based method that can be used to analyse labour in crop production systems and to quantify effects of system changes in order to increase the success rate of systems innovations. This method may also be valuable for decision support in case the system change concerns a change in labour management strategy.

If the model based method is realised, existing greenhouse crop production systems can be simulated, improvements can be analysed, and bottlenecks in operational processes can be identified. Envisaged solutions can be quantitatively evaluated without having to first build them. With this approach, requirements of new technology as well as business cases can be computed more easily and accurately.

1.3 Novelty of the research

Model based evaluation of labour in crop operations is relatively new in Dutch greenhouse horticulture. The number of sources in this area is very low. Various time studies and work methods analyses were done in the past (Hendrix, 1985; van Os, van Zuijdam, Hendrix, Koch, 1993; Gieling, van Henten, van Os, Sakaue, Hendrix, 1996; Schoen & Hendrix, 1996), but they hardly focused on modelling the labour and crop operations within the production process. Dutch examples of business process re-design and modelling of labour in greenhouses go back to the nineties. Annevelink (1992) described optimal space allocation in pot-plant nurseries using heuristic techniques. Leutscher, Renkema and Challa (1999) presented a simulation approach for modelling operational adaptations in tactical production planning of pot plant nurseries. More recently research on this topic was performed in Israel, where Eben-Chaime, Bechar and Baron (2011) used simulation to show that the pattern and length of worker routes affect the economic efficiency of a greenhouse. Bechar and Edan (2005), Bechar, Yosef, Netanyahu and Edan (2007), and Bechar, Lanir, Ruhrberg and Edan (2009) presented work methods analyses and simulation techniques to improve crop operations in Israeli greenhouses for production of sweet pepper, tomato, and Gypsophila respectively. Pratt (2008) reported on how to achieve efficient use of labour in protected edible crops production using lean manufacturing principles but no models were used. Currently, in Dutch greenhouse horticulture, no verified models for simulation of high tech crop operations are available and no examples are known of model based analysis and evaluation of crop operation scenarios.

However, model based system evaluation in greenhouse horticulture is not a new phenomenon. Simulation models for greenhouse climate prediction and energy performance date back to Bot (1983). Detailed dynamic greenhouse climate control and energy models have been developed in the years after (Rath, 1992; Zwart, 1996; Husmann & Tantau, 2001). Vanthoor (2011) demonstrated a model based optimisation of greenhouse design for different climatic regions with net economic result as an optimisation criterion. A multi-factorial optimisation problem on greenhouse design and climate equipment choice was addressed and solved. This work was based on long term development and fine tuning of greenhouse climate models. Modelling of production processes and labour processes in greenhouses was not initiated until the start of this research.

In industry, use of model based evaluation of manufacturing systems, logistics and management strategies is not new. Several model based management strategies are used like the business process re-engineering paradigm (Jansen-Vullers, Kleingeld, Netjes, 2008) and the Six-sigma paradigm (Hopp & Spearman, 2008). Re-engineering assumes that the organisation's performance is limited by the ineffectiveness of its processes. By removing bottlenecks the system performance improves. Six-Sigma aims to reduce defects in products and processes into the part per million range. Design for Six-Sigma has the methodology - define, measure, analyse, design, verify (Hopp & Spearman, 2008). Use of quantitative simulation models is not necessarily part of these management strategies, but simulation of integrated production processes is more common (Stevenson, Hendry, Kingsman, 2005). Lefeber and Rooda (2006) and Rooda and Vervoort (2004) discuss the modelling and analysis of manufacturing systems. A specific example is given by Detty and Yingling (2000), who carried out discrete event simulation experiments to improve an existing assembly operation by implementing lean manufacturing principles, which resulted in reduction of average order lead time, savings in equipment, personnel, inventory and floor space and in reduced variability in supplier demand.

Just as in industry, also in greenhouse technology, (re)-design for effective production processes benefit from a systems approach and an operations viewpoint as it promotes process logic and reduction of waste. Trial and error design should be prevented and a systems approach should be adopted to also keep focus on the function of the technological solution in the process. Historical key insights in using an operations viewpoint in design of industrial processes are (Hopp & Spearman, 2008):

1) *to include the production environment as a design control*, which means translated to crop operations that solutions must be embedded in the larger system of the physical (crop) environment and in the logistic environment of crop operations,
2) *to control the work in process for a smooth and rapid flow of materials through the system*, overloads and wait times should be prevented in both the greenhouse and the processing room.
3) *to use operational details for strategic decisions on process improvements*, for instance, if exposure of the cut point (strategic decision) delivers a 1 s gain per flower for millions of flowers ha^{-1} y^{-1} (operational detail) a substantial effect results at company level,
4) *to create process flexibility in order to respond to a volatile market*, for instance, adequate response to client orders using flexible product sorting and packing delivers better revenues than bulk production,
5) *to use quality and continuous process improvement as conditions for business survival*, total quality management should be a way of professional life.

These key insights were a guide in creating the model based evaluation method for labour and crop operations in greenhouses presented in this PhD thesis.

1.4 Research objective and model requirements

This research targeted on labour and crop operations in advanced high tech greenhouse horticulture production systems in North Western Europe, that produce cut-flowers or fruit-vegetables, where crop related processes are highly mechanised, but actions in the vicinity of the crop are performed manually, and where a potential need for further increase of labour efficiency exists.

The research objective was to obtain a good and quantified understanding of labour and crop operations in horticultural production systems materialised in a generic model based method. The purpose of this method is to analyse, simulate, and evaluate work methods and labour management scenarios in existing or redesigned greenhouse crop cultivation systems. From a societal viewpoint, this research seeks to contribute to effective greenhouse crop cultivation systems with efficient use of human labour and technology. Simulation of crop operations in greenhouse facilities should be possible from the viewpoints of the system designer in research and industry (see Section 1.1), the facility manager and the worker.

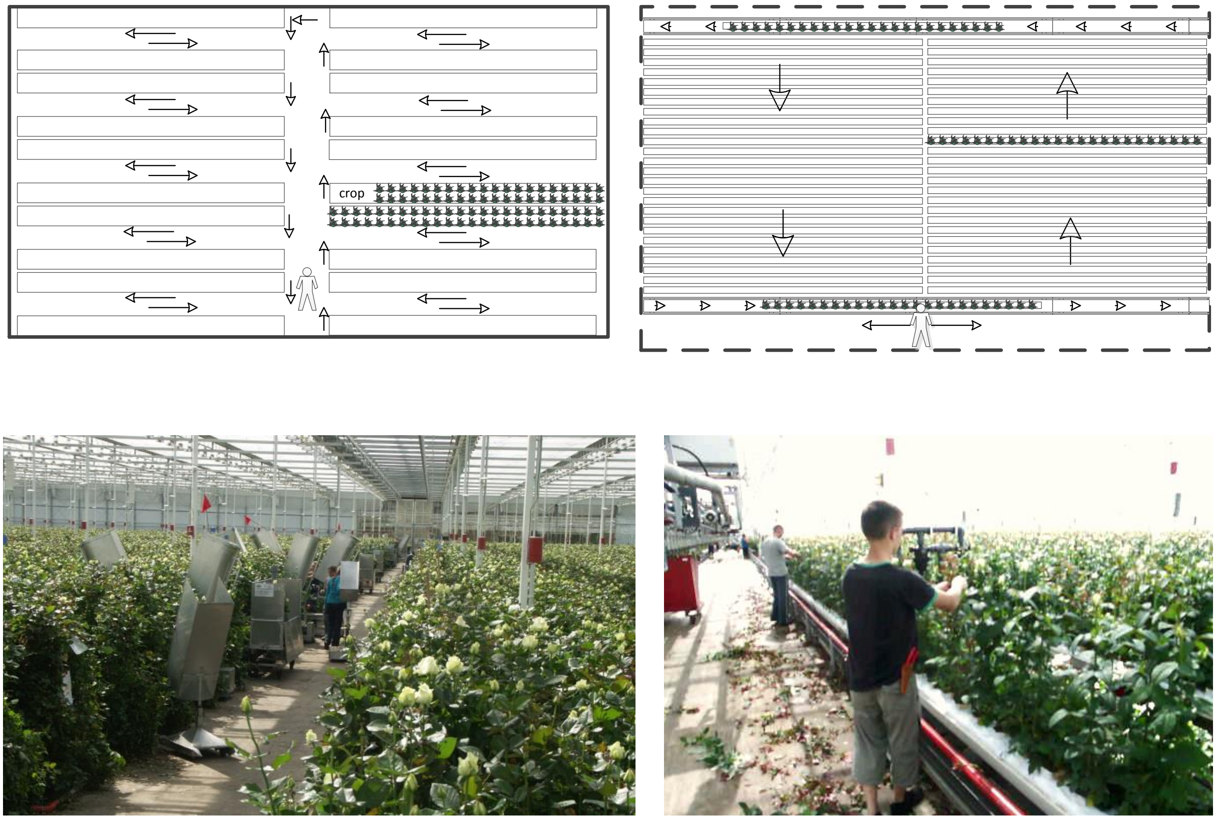
To allow simulations for these viewpoints, the model should have freedom of system definition with respect to 1) greenhouse layout, 2) crop cultivation system, 3) crop operations and work methods, 4) choice and use of human or material actors and choice of equipment (resources), 5) properties of (individualised) actors with respect to performance parameters. The complete set of functional requirements for the model based method is given in Table 1.1. The model output should reveal consequences of operational modifications in key performance indicators such as lead time, throughput of products, and (labour) time demand and labour costs. Lead time indicates the time allotted for execution of a task or the production of a part such as a full product buffer on a given routing. Throughput is the average product output of a crop operation per unit of time.

Table 1.1 Requirements for a model based evaluation method of crop operations in greenhouses.

Category		Model requirement
General	1	The model must support growers and designers in analysis and evaluation of design concepts for system innovation.
General	2	The model must contribute to interpretability, manageability and traceability of effects of innovations and labour organisation changes.
General	3	For structural changes in work methods and for new concepts the model must be able to show feasibility in simulation results before pilots in practice are needed.
Model paradigm	4	The model must give expression to the event based nature of crop operations.
System definition	5	The model must have freedom of system definition with respect to 1) greenhouse layout, 2) the greenhouse partitioning, selection of crop operations of interest, greenhouse sections of interest, and output of interest, 3) crop cultivation system, 4) crop operations and work methods, 5) allocation of constrained or non-constrained resources, 6) use of workers with individual or uniform equal performance parameters, 7) choice and use of both human or material actors and of equipment (resources).
System definition	6	Required crop specific harvest and maintenance tasks must be simulated in time and space.
System definition	7	The model must plan tasks effectively while crop operation frequencies are taken into account.
System definition	8	The model must assign operational actors and facilities to tasks for best practical execution of tasks.
System evaluation	9	Simulation instrument should be generic in order to support design effort while leaving the creation of new concepts to the designers.
System analysis	10	The model must reveal operational details for decisions on process improvement.
System analysis	11	Basic actions on individual plants and products must be chosen as the systems bottom level in order to show effects of function variation at action level in preparation for application of new technology.
System analysis	12	Operation of a full greenhouse must be the highest system level in order to evaluate effects of labour management.
System analysis	13	Allow sensitivity analysis for one or more parameters.
Output	14	The model must reveal consequences of modifications in the crop production system in key performance indicators such as lead time, cycle time, throughput, utilisation of operational resources, travel distance, and (labour) time demand and time components as well as labour costs.
Output	15	The model should produce timelines of workers, equipment use, crop operations and actions.
Output	16	The model should reveal time based signals of process variables to allow in depth analysis of crop operations.

1.5 Focus on rose crop production

The research was focussed on the crop cut-rose as a case study. This case was selected because rose presents a problem class representative for the intended domain of crops that require accurate and quick actions in crop operations, that are therefore done manually until the present day. First of all two crop cultivation systems exist in the Dutch horticultural practice, a static path based rose cultivation system, and a mobile system with rotating crop loops. These systems are shown in Fig. 1.1.



a b

Fig. 1.1 - Two crop cultivation systems in cut-rose production, the static path base rose cultivation system, overview of greenhouse (a) and the mobile system with rotating crop loops, overview of one crop loop (b).

In a static path based system the roses are grown in a substrate culture on gutters above floor level perpendicular to the main aisle. Between crop rows or beds small paths exist for access to the crop on foot or with (electric) trolleys which use the pipe rail heating system for transportation. The trolleys are used for transport of worker and product. This system is common in many vegetable and cut-flower crops like sweet pepper, tomato, cucumber, gerbera, and chrysanthemum. Of course differences exist with respect to crop architecture, plant morphology and the height position of the product, but work methods are quite similar when expressed in mathematics and in simulation.

In mobile growing systems, roses are on transportable gutters which move through the greenhouse within rotating loops. Crop operations occur in the main aisle(s) which may be positioned in the greenhouse centre or along the side walls. Outside these aisles the crop is not accessible. This system is similar to that of transportable tablets. A transportable crop is common for ornamentals. The routing of transportable units may differ per crop. For some mobile crops all crop operations are performed in or near the processing room. In cut-rose the mobile system was designed to reduce operator and product transport and to feed roses into the sorting line automatically by means of a conveyor, thus preventing bundling of roses in transport buffers.

A second reason to focus on rose is that harvesting is a daily activity but other crop operational tasks are planned in time and place based on crop monitoring or path visit frequency. Examples of crop operations to maintain the crop are disbudding, bending, breaking buds, and crop health monitoring. Other crops have similar crop operations. As a third reason, roses have a complicated crop environment where during harvest each ripe rose must be cut with maximum stem length without damaging the base of the plant and without reducing leaf area index. Also other crops have a complex and highly variable crop environment. Lastly, healthy well-tended rose crops produce millions of product units (flowers) per ha per year, also a feature commonly encountered in horticulture. Small effects per action may have big effects on the labour productivity and costs. All-in-all the rose is assumed to be a suitable representative of greenhouse grown crops on which a generic modelling paradigm can be built.

Greenhouse crop production systems are hybrid systems with both discrete event characteristics for human actions and continuous time characteristics for climate and crop growth. Crop operations in greenhouses were approached as a discrete event simulation problem. In this research the greenhouse climate, crop growth, and water and nutrients were not taken into account. The crop yield was used as a model input. Therefore, yield effects resulting from differences in crop operation scenarios other than measured were not included.

1.6 General approach

During this research a functional analysis of the crop production system was made, a process analysis of crop operations and product flow was carried out and a quantitative simulation model for labour and crop operations was developed. The modelling fully focused on the discrete event characteristics of the greenhouse production system. Fig. 1.2 presents an outline of the general approach. In order to create the proposed method, several crop operations were subjected to a functional analysis in IDEF0 and a process analysis in IDEF3. IDEF0 and IDEF3 are both members of the IDEF-methods family (Integrated Definition) (Kusiak, Nick Larson, Wang, 1994; Mayer et al., 1995; Jeong, Cho, Phillips, 2008). In order to collect model input data and datasets for model validation several greenhouses were monitored. The acquired data originated from video observation and from labour registration systems. Next to IDEF0 and IDEF3 modelling and data analysis, a generic model was developed capable of analysing and evaluating work methods and process scenarios in greenhouse crop operations. The first generation model for simulation of crop operations included labour, labour management, process operations and product flows. Therefore, the model was named GWorkS, an acronym for Greenhouse-Work-Simulation. Crop operations in greenhouses are mainly event based as they are initiated by a timed release of planned tasks to the system (time-driven), followed by a chain of operator actions within crop operations which are identifiable as chains of events (event-driven). This combination of time-driven and event-driven model activity is typical for a discrete event system (Cassandras & Lafortune, 2010). The model core was therefore developed as a discrete event system. The model was implemented in Matlab®, Simulink®, and SimEvents®.

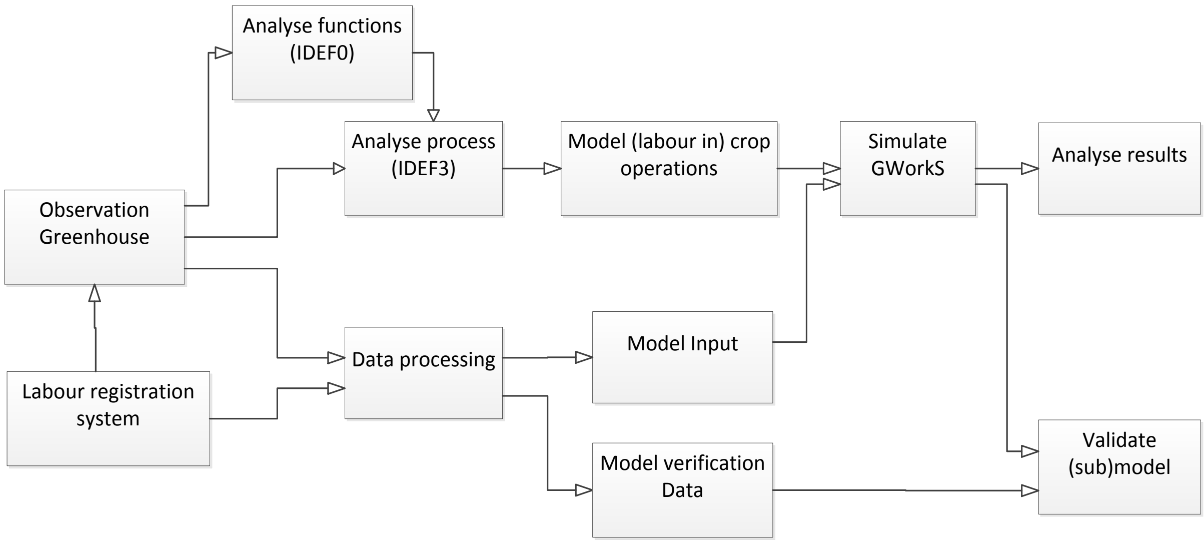


Fig. 1.2 - Outline of the general materials and methods and problem approach.

Simulation results were expressed in terms of performance indicators known from operations research (Hopp & Spearman, 2008), such as lead time, cycle times, throughput, utilisation of human and material resources, and (labour) time demand and costs. Also timelines of operators in actions were produced to provide input for analysis, just like time logs in labour registration system. To bring added value and wastes of crop operation concepts to surface, in system analysis the most detailed system level was chosen to be a basic action on an individual plant or product, such as cutting a stem or placing a product in a buffer, to find effects of function variation at action level. The most aggregated system level was chosen to be the operation of a full-scale greenhouse in order to expose quantified effects in key performance indicators for the greenhouse as a whole.

The GWorkS model was developed in steps to address both the research objective and the requirements (Table 1.1):
1) scheduling of crop operations in time and place for a representative daily workload (requirements 1, 7),
2) realisation and verification of the model for harvest in mobile and static rose cultivation systems to create flexibility with respect to crop cultivation systems (requirements 5.1-5.3, 9),
3) realisation and verification of the model for different types of crop operations to create flexibility in work methods and to test the model for its accuracy (requirement 4, 5.4, 6, 10, 11),
4) prepare the model for sensitivity analysis to find most relevant parameters for system modification (requirement 3, 13, 14),
5) prepare the model for constraints with respect to available resources in crop operations to find optimal use of resources and because in practice, resources are never unlimitedly available (requirements 5.5-5.7, 8),
6) prepare the model for integrated simulation of several crop operations to reflect the logistic complexity of an operational greenhouse (requirements 6, 7, 12),
7) prepare the model for scenario simulation and scenario selection to support decision processes in business process redesign (requirements 2, 6, 12).

1.7 Research questions

The following research questions were addressed in the consecutive research Chapters:
1) Is the proposed model paradigm of discrete event systems able to represent the harvest process in a mobile rose production system in a greenhouse accurately and is it able to determine best settings for basic system parameters? (steps 1, 2),
2) Is the generic approach of the model also applicable to represent the harvesting process in a static rose production system in a greenhouse? (steps 2, 3),
3) What sensitivity analysis method is adequate for a discrete stochastic dynamical system, the GWorkS-model? For which parameters is the model most sensitive? (step 4),
4) Is it possible to point out the most effective labour (management) scenario in a finite set of scenarios in case of integrated full scale simulation of multiple crop operations with the GWorkS-model? Can the model handle a multi-factorial scenario assessment? (step 5-7).

1.8 Outline

This section gives an outline of the thesis and shows how the thesis Chapters relate to the research questions and the model requirements.

Chapter 2 addresses research question 1 and model requirements 1, 4, 5.1, 6, 7, 10, 11, 14 & 16. In this Chapter, the GWorkS-rose model formalism and structure is presented with emphasis on definitions, model hierarchy, and description of model inputs, outputs and main structure. Greenhouse operations were defined as a job-routing system and job management was given shape in a job planner. This first model version was validated for the case of one or two harvesters operating one crop loop in a mobile rose cultivation system from the main aisle of the greenhouse. All moving objects in the system were modelled in the discrete event simulation core of the GWorkS model. Service times of basic human and system actions in crop handling were described as user definable probability density functions. The model was used to find best settings for operator and mobile gutter velocity.

Chapter 3 addresses research question 2 and requirements 1, 2, 4, 5.1, 5.3, 5.4, 6, 7, 10, 11, 14 & 16. In this Chapter, the generic and flexible model approach was tested by applying the GWorkS-rose model with limited modification in simulation of the harvest process in a static cut-rose production system. The limited modification was described as a set of specific model extensions. These necessary extensions were the coordinate system of path based greenhouses, calculation of travel distance of operators, to allow high job frequency, a flexible definition of greenhouse locations, multiple operators in one greenhouse section, parallel execution of basic actions, and operator decisions in paths and at path completion. The model was validated for a single greenhouse section of 1800 m^2 for one harvester during one week and for a period of 3 months with more active harvesters and a large range in rose yield. The model flexibility was tested by simulating different harvest scenarios showing effects of average worker skill, equipment choice and harvest management.

Chapter 4 addresses research question 3 and requirements 1, 5.1, 5.3, 6, 13, 14 & 16. In this Chapter, the model was subjected to a sensitivity analysis for the case of the static cut-rose production system. Parameters with strong influence on labour performance were identified as well as the effect of uncertainty in parameters on key performance indicators as labour time, throughput, cycle time of greenhouse sections and paths and travel distance. In sensitivity analysis a comparison was made between the one-at-a-time differential sensitivity analysis (DSA) and Monte Carlo analysis (MCA), since in the GWorkS-model is a stochastic model where internal random processes may disturb the DSA-result. If both methods agree with respect to total sensitivity, then DSA is a credible and fast method fit to be used to determine sensitivity of model outputs for individual parameters.

Chapter 5 addresses research question 4 and requirements 1, 2, 3, 4, 5.1-5.7, 6, 7, 8, 9, 10, 11, 12, 14, 15 & 16. In this Chapter, the GWorkS-model was brought to the level of integrated simulation of more crop operations executed by many workers at full scale for a 3.6 ha greenhouse. Next to harvest also disbudding and bending were analysed. The objective was to determine the feasibility of the GWorkS-model for simulating and ranking labour management scenarios in a cut-rose greenhouse. Eight labour management scenarios were simulated and ranked including a real labour management scenario as applied in a Dutch cut-rose grower company. The focus was on integrated simulation of the crop operations harvest, disbudding and bending. Secondary objectives in this study were to verify the submodels for bending and disbudding, to prioritise crop operational tasks, and to prioritise resource allocation for crop operations. The model was extended for simulation of multiple greenhouse sections, multiple operators active in several crop operations under a limited number of workers and equipment. The job planning, job routing, resource allocation, the prioritisation of tasks in time and place and simultaneity of task execution were tested in scenarios relevant for practice and challenging for the model. The underlying research questions related to worker skill and operational management of crop operations.

In Chapter 6 the results of this work are discussed in view of the research objective (Section 1.5). The future perspective of this work is discussed and recommendations for performance improvement and generality of the method are given.

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Chapter 2

GWorkS - A discrete-event simulation model on crop handling processes in a mobile rose cultivation system

A. van 't Ooster, J. Bontsema, E.J. van Henten, S. Hemming

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2 GWorkS - A discrete-event simulation model on crop handling processes in a mobile rose cultivation system

2.1 Abstract

Mobile rose systems are designed to increase labour efficiency. However, many questions remain on best design and settings of operational parameters for best performance. The ultimate goal of this research is an assessment of re-designed horticultural crop production systems and work scenarios on labour and machine performance before implementation. To attain this goal, a queueing network model, GWorkS[1]-rose, is presented for simulation of labour processes in a greenhouse with a mobile rose cultivation system. The objective for modelling is to quantify effects of production system changes by means of a flexible and generic model approach. A state of art mobile rose production system was used to validate and test the GWorkS-rose model. Data from the labour registration system and from video recording were used for validation. System performance was simulated and compared to the performance measured in the real situation. Results of a single day validation show that the model estimates harvest labour time with an accuracy of 94%. For a one month validation an accuracy of 92% and RRMSE of 18% resulted. The value of RRMSE was caused by missing data on the number of workers at the loop and on the actual gutter speed level. The model can determine best system settings as is illustrated for operator and mobile gutter speed settings at given rose yield levels. It is concluded that the model can be used for studies on design and management of this kind of production systems.

[1] GWorkS is an acronym for Greenhouse Work Simulation, it is a discrete event simulation model on the crop handling processes and logistics inside a greenhouse production site.

Nomenclature

A_L	Floor area allocated per loop (m^2), equal for all loops
C_{hb}	Buffer capacity of 'hand buffer' in units of product
C_{hbm}	Tolerance buffer capacity in units of product at the end of a gutter
C_o	Individual harvest rate of an operator (stems h^{-1})
$CT\ (L,k)$	Cycle time on task k in loop L (s)
CT_L	Cycle time of node L (s)
d	Local distance to next point of action (m)
$D+$, $D-$	Direction of the operator movement. D+ is opposite to direction of gutter movement, D- is in direction of gutter movement
D_e	Cumulative travel distance since t_0 of relevant entity e (m)
$E(n)$	Expectation of variable n
g	Index to indicate a gutter parameter
G	Index of a gutter (subnode), $G=1,\ldots,n_G$
$G_f(k)$	Index of first gutter to be processed within task k
$G_{fr}(L)$	Index of the gutter positioned at the workspace in loop L (front gutter)
$G_l(k)$	Index of last gutter to be processed within task k
J	Job status table, $n_L * n_G * (n_P+1)$ matrix
$J(L,G,k)$	Job element k to be executed in subnode G of node L
J_{Fn}, J_{Fsn}	Greenhouse specific frequency of job execution at node (n) and subnode (sn) level (d^{-1}), $n_T * n_P$ matrices
J_H	Job history table, time since last job execution (d), $n_L * n_G * n_P$ matrix
k	Index of the job element executed, $k=1,\ldots,n_P+1$
L	Index of a crop loop (node), $L=1,\ldots,n_L$
LCS	Lack of correlation, weighted by the standard deviations (Kobayashi & Salam, 2000)
l_g	Gutter length (m)
$LT(L,k)$	Lead time on job element k in loop L, a management constant indicating target process time
n_G	Number of gutters per loop, equal for all loops
$n_G(k)$	Number of gutters to be processed in task k
$n_{G,L,2o}$	Number of gutters in loop L, processed by two operators simultaneously
n_L	Number of loops in the greenhouse
$n_{o,L}$	Number of operators needed at loop L
n_P	Maximum number of job elements per node
$n_{r,L,G}$	Stochastic variable number of ripe stems per gutter G in loop L
n_{rB}	Number of rose entities in the buffer queue
n_T	Number of time periods in a year
o	Index to indicate an operator parameter
$P_e(t)$	Time logged positions of relevant entity e (operators and gutters)
$p_\nu(\nu)$	Probability density function of the stochastic variable ν
$P_{r,L,G}$	Stochastic variable position of ripe stems on gutter G in loop L
P_r	List of coordinates reference positions for operators
r	Correlation coefficient
A_L	Floor area allocated per loop (m^2), equal for all loops
$RMSD$	Root mean square deviation
$RRMSE$	Relative root mean squared error
SB	Squared bias, squared difference of means (Kobayashi & Salam, 2000)
SDSD	Squared difference between standard deviations (Kobayashi & Salam, 2000)
t	Time (s)
$T_0(L,k)$	Raw process time on job element k in loop L (s)
t_0, t_f	Start and end date of simulation
$T_B(k)$	Time intervals where execution of all k^{th} job elements is blocked
T_{cr}	Stochastic variable service time to cut a single rose (s)
T_{ge}	Stochastic variable service time to exchange gutters in the workspace (s)
$TH\ (L,k)$	Throughput of product, average output of task k in loop L per unit time (h^{-1})
T_{pd}	Stochastic variable service time to deliver a single rose to the main conveyor system (s)
$T_T(L,k)$	Total labour time on task k in loop L (s)
$T_{Ta}\ (L,k)$	Total action time within task k in loop L (s)
T_{tl}	Stochastic variable service time to change the gutter speed status to maximum speed level (s)
T_{ts}	Stochastic variable service time to change gutter status between moving and still (s)
$T_{Tt}\ (L,k)$	Total transport or move time within task k in loop L (s)
$T_{Tw}\ (L,k)$	Total wait time within task k in loop L (s)
u_G	Step control gutter velocity v_g
u_s	Utilisation of service station s
v_g	Gutter velocity (m s^{-1})
v_{gL}	Discrete levels of gutter velocity (m s^{-1})
v_{gS}	Status of the gutter speed, M= moving, S= still.
V_g	Vector with specific gutter velocities in workspace [0 v_g v_{g_max}]
v_{g_max}	Gutter velocity when gutter is send off for exchange (m s^{-1})
v_i	Velocity of object i (m s^{-1})
v_o	Operator velocity task execution (m s^{-1})
v_{ow}	Operator speed when walking between facilities (m s^{-1})
V_o	Vector with specific operator velocities [v_o v_{ow} v_{o_max}]
v_{o_max}	Maximum value for v_o (m s^{-1})
WD	7 element array identifying the workdays of the week
x	Length coordinate of a gutter G (m)
x_{tol}	Tolerance in x, allowed gutter movement during a rose cut (m)
Y_L	Daily yield per loop (stems m^{-2})
$\eta_C(k)$	Trigger signal indicating a task k is completed
$\hat{\sigma}_\nu$	Estimated standard deviation of stochastic variable ν

2.2 Introduction

Economy and labour are internationally stated as the top driving forces for innovation in greenhouse horticulture in high income countries (Giacomelli, Castilla, van Henten, Mears, Sase, 2008). High labour productivity is required to sustain production in high income countries under rising prices of resources, and under competition on international markets where also emerging countries operate. Mechanization and automation are considered as ways to improve labour productivity (Van Henten & Kruize, 2008). In the past decennium, mobile growing systems for roses were implemented as an answer to the increasing demand for labour efficiency (Van Henten, 2006). The design paradigm shift in this mobile system was to transport the product instead of the more time critical operators and equipment, analogue to systems used in industry and analogue to internal transport systems in for instance pot plant production. Compared to standard static growing systems, in practice labour efficiency improvements of more than 25% were claimed for the mobile system. Potentially, the mobile rose production system simplifies steps in greenhouse automation, such as crop protection, product transport, and robotic harvesting (Noordam et al., 2005; Van Henten, 2006; García Victoria, Eveleens, Van Telgen, Van Weel, 2007). In the Netherlands, about 10 rose producers implemented the system during the last decade, but acceptance of this technology is slow and some of the companies using this technology stopped for reasons not understood.

For mobile growing systems, many questions remain with respect to design and operational parameter settings such as the ratio between total crop area and the number of work stations, the relation between crop yield and gutter speed, capacity of the conveyor system and sorting installation. Currently decisions are not based on quantitative comparison of systems or system settings. Reports on labour studies and observations exist, but lack a model based quantitative system evaluation. Previous work on simulation of crop handling processes in greenhouses is scarce. Mainly in Israel simulations were conducted on work methods in greenhouse horticulture (Bechar & Edan, 2005; Bechar, Yosef, Netanyahu, Edan, 2007; Bechar, Lanir, Ruhrberg, Edan, 2009).

In order to provide industry and practice with answers to the stated type of questions, a simulation model on labour processes in a greenhouse was developed and validated. The main objective of our research is to develop a design tool able to quantify effects of production system design by means of a flexible and generic model approach.

An important prerequisite to fulfil the main objective is a mechanistic model of crop handling processes. The method used in modelling crop handling processes follows the paradigm of queueing theory (Cassandras & Lafortune, 2010), where processes are represented by a discrete event system. This paper describes a model of one loop of a mobile rose production system. The system and the model are described in Section 2.3. Materials and methods for parameterisation and validation are described in Section 2.4, and model validation results and examples of the added value of the model in Section 2.5.

2.3 A model of a mobile cut rose growing system

2.3.1 Systems description

In a standard rose growing system in the Netherlands the roses are grown on gutters at 0.5 to 1 m above floor level. The gutters are oriented perpendicular to the main aisle and groups of 4 gutters are separated by small paths for crop operations. In mobile growing systems for roses, the gutters move through the greenhouse and crop operations occur in a central place. The layout of a greenhouse with a mobile growing system is shown in Fig. 2.1.

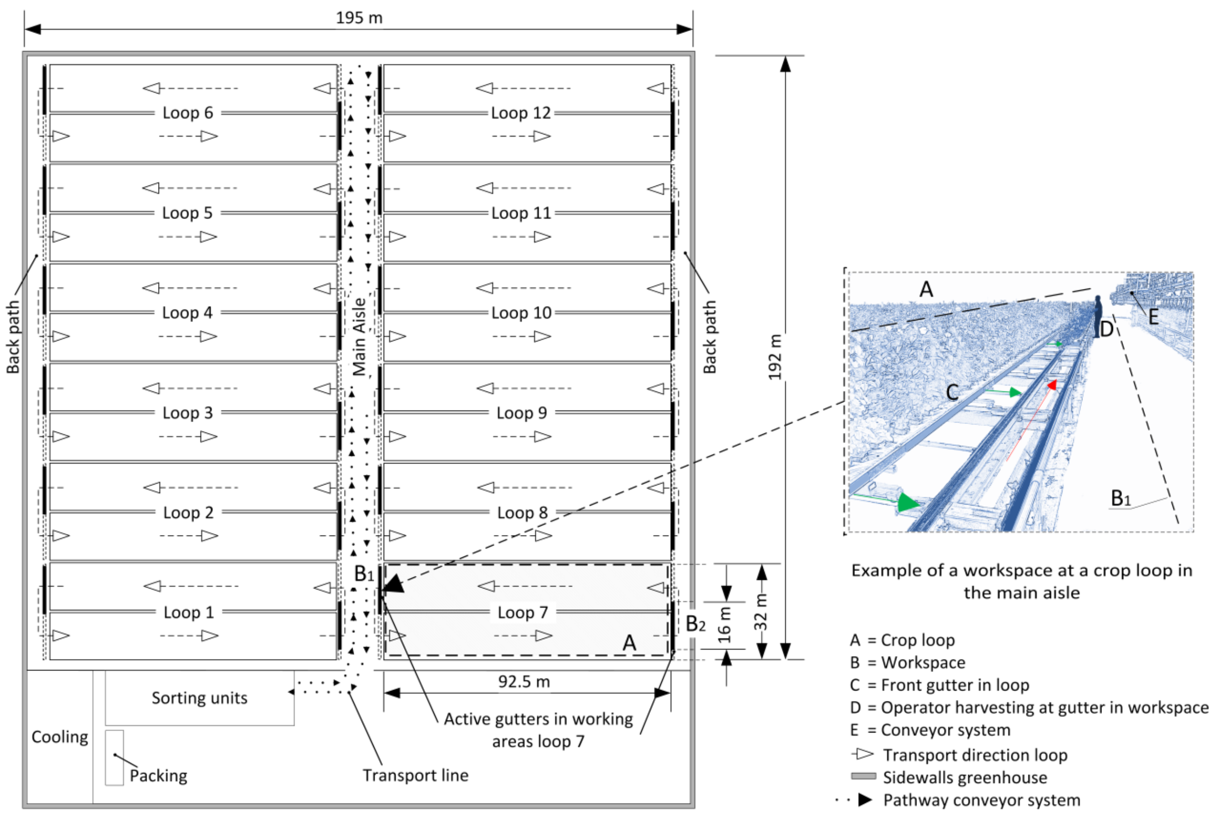


Fig. 2.1 - Layout of the functional area of the mobile growing system for cut roses.

The greenhouse is divided in equal sized sections. Two adjacent sections form a counter clockwise rotating loop (A). In the main aisle, and at the back path, gutters are transported on a conveyor belt. The space along these conveyors is the workspace of the personnel. The processes harvest, pruning and disbudding take place at the main aisle (B1), bending of unproductive stems and crop protection is executed at the back path (B2). In a moving system, the gutter (C) is oriented parallel to the main aisle with a gutter length of 12 – 16 m and an effective gutter width of 0.65 – 0.75 m.

A gutter is processed when it reaches an employee in the working space. At the start of a process, the gutter speed is set to match the employee's skill and workload. The worker has the option to halt the gutter, if the process is too fast. At one gutter maximal two workers can be active. The harvest of the roses is performed one handed with scissors that both cut and hold the rose stem. The other hand holds the cut roses as a temporary buffer. When all ripe roses on a gutter are cut or when the buffer hand is full, the roses are one by one placed in a transport unit of the conveyor system (E), which feeds the stems into the sorter machine.

2.3.2 Modelling formalism

In order to model the system described in Section 2.3.1, the human and mechanised action within the mobile growing system is defined as a discrete event system (Schriber & Brunner, 2000). Crop growth and production, and the resulting need for crop handling actions were measured at a commercial grower.

2.3.2.1 Definitions

A discrete event system consists of abstract units of traffic, entities. Entities are service requesting objects that move within the system between service points, servers, while they compete for the use of resources (Schriber & Brunner, 2000). In servers operations are executed. Claassen, Hendriks and Hendrix (2007) define an entity as any object or component in the system that requires representation in the model. The model defines entities for all system components that contribute to required actions in servers. The main entities are jobs. A job is a set of planned crop handling operations at a planned location (node) using planned workers and facilities (resources). For each node a job is generated with node number and operations to be executed on the current day as attributes. Attributes are properties of an entity. A single process is a job element. Executing a job element is a task. A job element will only be executed if node and resources are simultaneously available at a server. A server can also be a task representing subsystem. A subsystem is a coherent combination of model elements to be executed upon occurrence of specific events. An example of a task is the actual harvest (job element) of all gutters within one loop (node) by a single worker (resource). A task breaks down into subtasks and subtasks into actions. A subtask of harvesting is to cut roses at a single moving gutter (subnode) within the workspace. An action is to cut a single rose. The system is defined in model levels representing a top-down system hierarchy: greenhouse (system), loop (node), moving gutter (subnode), and rose plant (place of action) (see Fig. 2.1). A cut rose is a product. Nodes, subnodes, product, and workers are all represented by entities. All entities have data for logistic operations, calculation of deterministic process times and reporting. In order to describe the system dynamics, the process oriented simulation scheme is used as described by Cassandras and Lafortune (2010). The defined terms entity, job, job element, system, subsystem, node, subnode, resource and action represent the generic level of the model, whereas terms like loop, gutter, rose plant, workers represent the physical growing system.

2.3.2.2 Model hierarchy

The model follows the system hierarchy. The greenhouse is represented by a series of subsystems, named node models. The node model describes a single crop handling process at a loop by means of a network of queues, servers and logical operators. Details are given in Section 2.3.3.4. A job is executed or queued upon arrival, where for example the subtask "harvesting a single gutter", is executed if the *resource* (harvester) and *subnode* (gutter) coincide in the workspace. At the level of a place of action, a rose cut action is executed if the position of the harvester (*resource*) and the rose (*place of action*) are within radius of action of the arm of the harvester.

A single rose starts as a gutter attribute indicating the rose position, and becomes a *product* when cut. This product is buffered in a queue for further processing in model section *product handling*. The presented model describes the harvest operation till delivery of the cut roses at the transport line in the main aisle.

2.3.3 GWorkS model description

The main structure of the model for roses, named GWorkS-rose, is given in Fig. 2.2. For the model we assume: 1) predefined crop handling operations that are executed at a periodically fixed time interval, 2) stochastic variables $p_V(v)$ to describe service times of basic human actions, 3) no individual differences between trained workers, 4) stochastic variables $p_V(v)$ to describe the number of actions and places of action per subnode, 5) that velocities take a limited set of fixed values only. Sections 2.3.3.1 to 2.3.3.4 respectively describe the model inputs, job management, the model outputs, and the discrete event simulation core of the model.

2.3.3.1 Model inputs

The user enters input parameter values on dimensions of the greenhouse and the growing system, on the crop loop to be simulated, and on run settings like the simulation period or a parameter range. Daily yield per loop Y_L in ripe stems m^{-2} and greenhouse specific frequency of job execution J_{Fn} and J_{Fsn} is used as input data to synchronise the simulation with the actual management and yield of the production site. The probability density functions on processing times of basic actions as determined from measured data are also used as model inputs. Examples of basic human or machine actions are 'cut rose', 'hang-in rose' and 'exchange of gutters to work area'. Transport times are defined deterministically based on distance d and speed v. Velocities of men V_o and machine parts V_g, and coordinates of reference positions P_r, like the start position at the gutter and the product unload position, are model inputs. Other inputs are buffer capacities, positions of facilities, and initial system state. Optionally target times for node cycle times $LT(L,k)$ may be set. The model inputs are shown in Fig. 2.2.

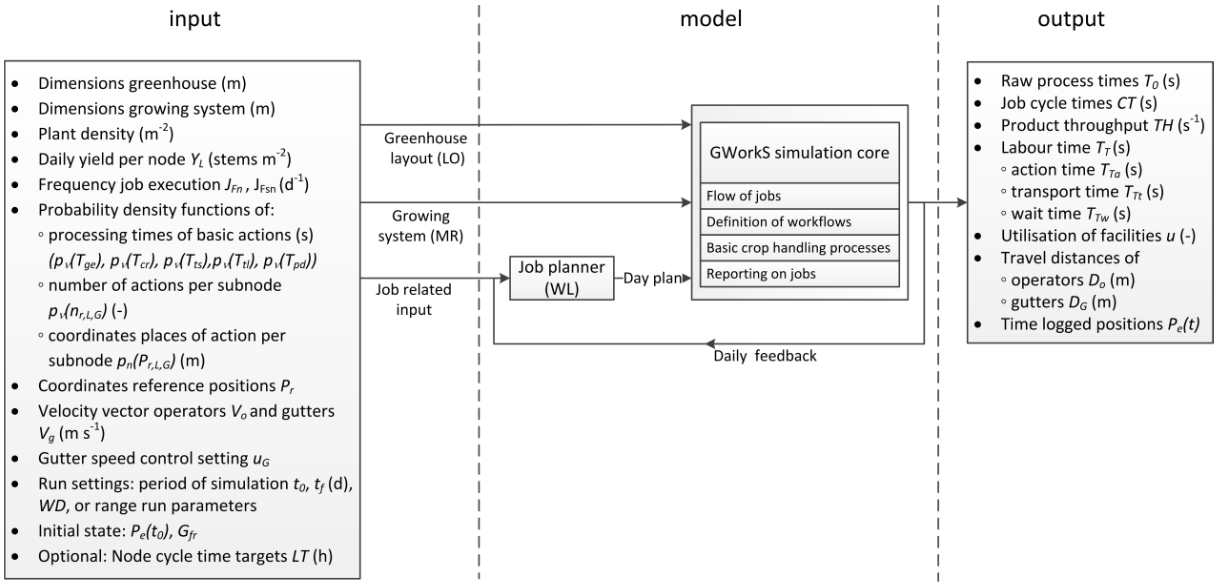


Fig. 2.2 - Structure of the model GWorkS-Rose. Inputs are converted to a full definition of greenhouse layout (LO) and crop production system (MR=mobile rose). The job planner or work load planner (WL) and the GWorkS simulation core form the model.

The model input is used to initiate the discrete event simulation and to set parameters associated with the greenhouse layout (LO), the production system (MR), and work planning. LO holds all relevant greenhouse dimensions. MR defines the physical layout of the loops and gutters, plant density, daily crop yield per loop, and frequencies of crop handling actions. Loops are identified with index $L=1,\ldots,n_L$, with n_L being the number of loops in the greenhouse. A_L is the floor area allocated per loop. Gutters are indexed with, $G=1,\ldots,n_G$ with n_G being the number of gutters per loop. Two probability density functions were used to assign ripe stems to gutters $p_V(n_{r,L,G})$ and to position stems at unique gutter locations $p_V(P_{r,L,G})$. A normal distribution was used to predict the number of ripe stems per gutter G. Parameters were the expected number of roses per gutter, $E\left(n_{r,L,G}\right)=Y_L A_L / n_{G,L}$ in loop L, and estimated standard deviation $\hat{\sigma}_{N_{r,G,L}}$. A uniform probability density function was used to randomise the position of ripe stems on gutter G, by assigning a unique coordinate value $x \in \left[0:l_g\right]$ with l_g being the gutter length.

2.3.3.2 Job management

The model itself consists of the job planner and the GWorkS simulation core (Fig. 2.2). The job planner defines the workload in the greenhouse on a daily basis by administrating a job status table J and a job history table J_H. It calculates what jobs need to be done during a day, based on job frequency and job history. Input parameters for the job planner are the job frequency table J_F, the workdays of the week WD and inactive times for each crop handling process $T_B(k)$, start and end date of simulation t_0 and t_f. Inactive times are time spans where no work is done on a specific process, as a result of priority, nights or breaks. The job planner produces a collection of jobs for the current day, defined as the job status table, a $n_L * n_G * (n_P + 1)$ matrix, where n_P is the maximal number of job elements per node L, $n_p + 1$ is the job element 'Node completed'. This job status table defines jobs at loop (node) and gutter (subnode) level. $J(L,G,k) = 1$ if a job element k must be executed in subnode G of node L. A second $n_L * n_G * n_P$ matrix J_H keeps track of the job history, that is the number of days since the job, $J(L,G,k)$, was executed the last time. The job status table and the job history table are used to tune the required job frequency with job execution at given capacity restrictions on resources, like for instance under capacity in the number of operators. For this tuning, the model either forces completion of the planned jobs J as in rose, or it returns unfinished work to the job planner for processing on the next day. Optionally, the job planner uses a target time for raw process time $LT(L,k)$ of each node and an expected individual operator work rate $E(C_o)$, to set a variable on the number of operators needed at a node $n_{o,L}$ or on the number of subnodes operated by two operators $n_{G,L,2o}$.

2.3.3.3 Model outputs

The GWorkS-core of the model performs the actual process simulation. The model output is depicted in Fig. 2.2 and subdivided in time related data $T_0(L,k)$, $T_T(L,k)$, $T_{Ta}(L,k)$, $T_{Tt}(L,k)$, $T_{Tw}(L,k)$, $CT(L,k)$, $TH(L,k)$, u_s, and space related data D_e, $P_e(t)$.

2.3.3.4 Discrete event simulation core of the GWorkS-model

The main structure of the GWorkS-core is a job routing system as depicted in Fig. 2.3 based on the tasks harvesting (1), disbudding (2), bending (3), combined harvesting (main aisle side of loop) and bending (backside of loop) (4), and combined disbudding (main aisle side) and bending (backside) (5), which are in this model called service stations.

The subsystem *Job generation* (A) generates job-entities based on model input (Fig. 2.2). Each job-entity represents a node with a list of m tasks to be executed during the current day. The job-entities enter the *Distribution Centre* (B), which manages the routing of the job-entity and reports on completed jobs. A job-entity is prepared for execution by sending the job-entity to a *Service Station* dependent on the current task in the task list $J(L,G_f{:}G_l,k)$, with ($0<G_f \leq n_G$; $0<G_l \leq n_G$). The service stations around the distribution centre contain one or more node models, a queue and a curfew function. A job-entity sent to a service station is queued for execution. Reasons for job delay are, the station is already running at full capacity, or no work is done during specific hours. Fig. 2.4 illustrates this for service station (1), harvest. When a job is completed, the job-entity returns to the distribution centre for the next task (k+1) in the list. When the task list is completed, the job-entity is passed on to the entity sink *Node completed* (C).

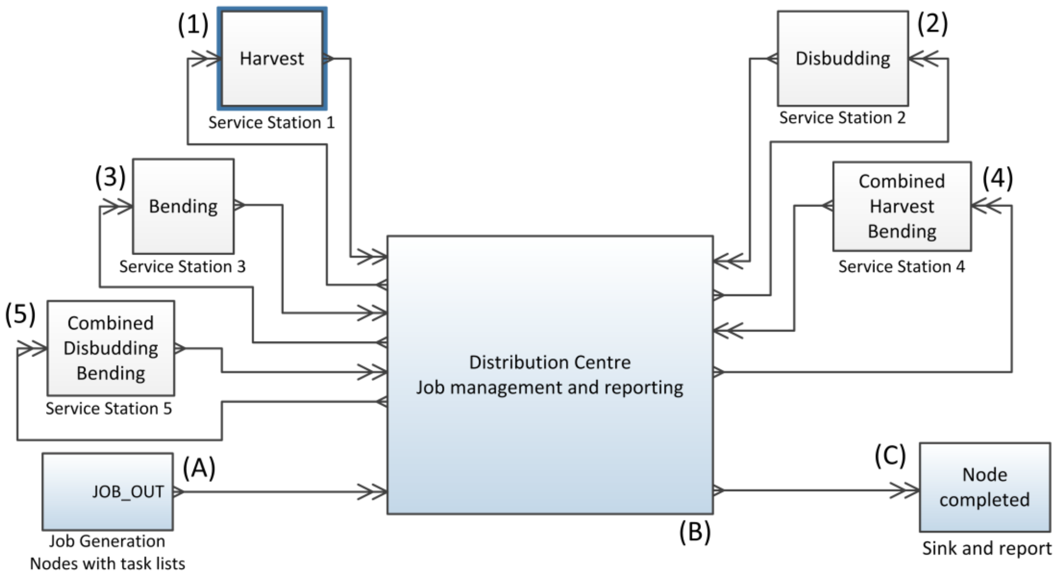


Fig. 2.3 - Main structure of GWorkS-core for day-to-day simulation of crop handling processes and internal logistics. It represents a distributed processing of tasks with 5 service stations: 1) harvest, 2) disbudding, 3) bending, 4) synchronous harvest and bending in one loop, 5) synchronous disbudding and bending in one loop. (⤳) indicates an entity path; subsystem(s) outlined bold are detailed in a new Figure.

Parallel execution of two tasks in one node is not possible in this model unless both tasks are defined as one integrated task as done in service stations (4) and (5). Parallel execution of different nodes is possible by introducing more 'Mobile Rose Harvest' node models (Fig. 2.4). Job-entity attributes determine the value of the output switch *S*. The job-entity raw process time $T_0(L,k)$ is measured and registered at this level.

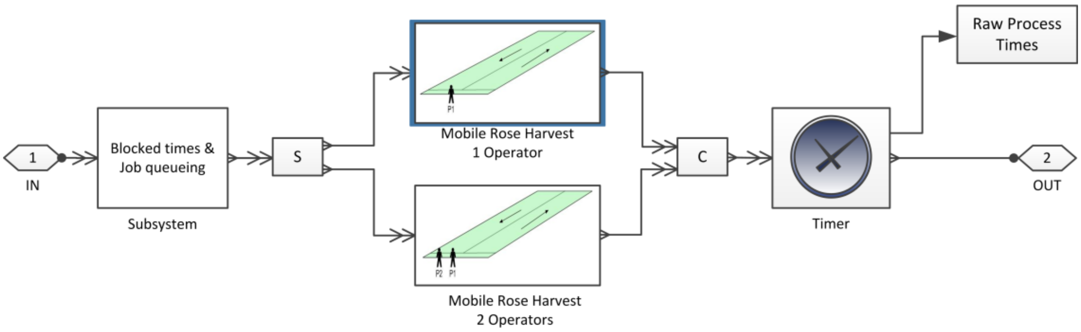
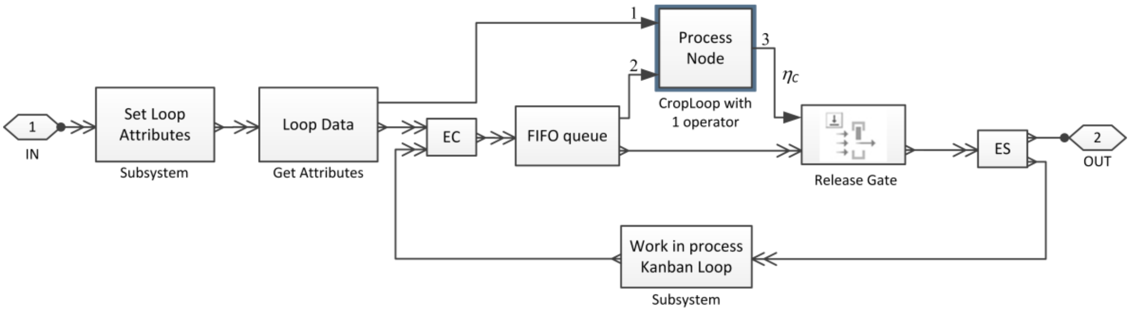
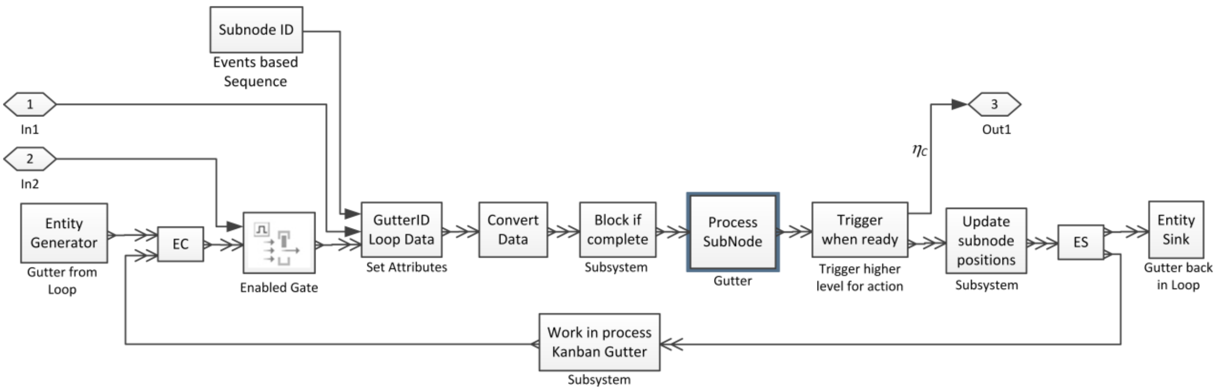


Fig. 2.4 - Model structure of service station 1 in Fig. 2.3. (⋙) entity path, S= output switch, C= entity path combiner.

The subsystem *Mobile Rose Harvest 1 Operator* (Fig. 2.5) processes a loop or part of it using one harvester in response to attributes carried by the job-entity. Loop attributes are loop index L, index of gutter to start with G_f, number of gutters (subnodes) to be processed $n_G(1)$, and current rotational position of the loop indicated by the index of the front gutter $G_{fr}(L)$.



a) Subsystem *Mobile Rose Harvest 1 Operator* in Fig. 2.4



b) Subsystem *Process Node* in a)
Node signals enable flow of n_g subnodes (gutters); when completed, a trigger signal is sent.

Fig. 2.5 - Nested subsystems of service station 1 to accept a loop for processing (a), and to subsequently generate and process subnode entities for gutters (b). (⋙) entity path, (⟶) signal, EC is an entity combiner, ES is an entity splitter.

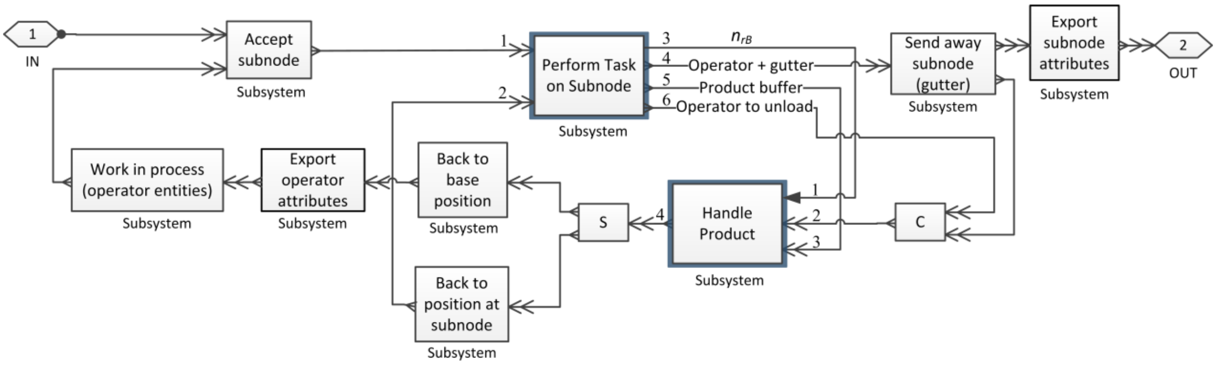
In Fig. 2.5a the job-entity is accepted and migrates to a loop-entity in *Process Node* where additional decision variables on the progress of task (k) in loop (L) are assigned as attributes.

The job-entity can enter and migrate only, when authorised for execution. This is implemented by introducing a Kanban-entity as used in 'Lean management' (Hopp & Spearman, 2008). When available, the Kanban-entity authorises a new job to be executed. It is released at initiation and when a loop-entity leaves the OUT-port. While the loop-entity is processed, the job-entity is held by the *Release gate*, which blocks entities until triggered by the input signal η_c. The input signal triggers when the task *Process Node* is completed.

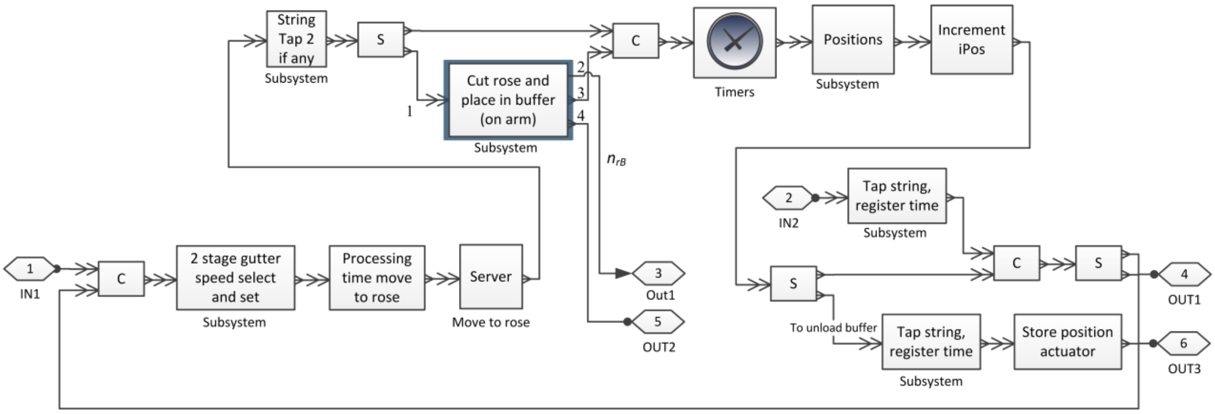
Inside the subsystem *Process Node*, the loop is broken down to n_G mobile gutters (Fig. 2.5b). For each gutter a subnode or gutter-entity is generated and provided with gutter attributes. These entities, G_f to G_l, are processed one-by-one in the subsystem *Process Subnode*. This model level keeps track of the number of gutters processed, updates the gutter positions inside the loop and sends out a trigger η_c to port Out1, when the planned number of gutters $n_G(k)$ has been processed.

In Fig. 2.6 the subsystems to process a gutter are given. The model scheme of the subsystem *Process Subnode* (Fig. 2.5b) is detailed in Fig. 2.6a. This subsystem accepts a gutter-entity to the processing area in *Accept subnode*, where the worker-entity and the gutter-entity are combined. This is followed by the actual harvesting in *Perform task on Subnode,* where the output consists of three entity types and a logistic signal n_{rB} indicating the number of roses buffered in the free hand of the harvester with buffer capacity C_{hb} roses and tolerance C_{hbm} when active at the gutter end. The output entity types are the combined operator-gutter entity (outputs 4 and 6) and batches of harvested product contained in the hand buffer (5) for final unloading (4 and 5) or intermediate unloading (5 and 6).

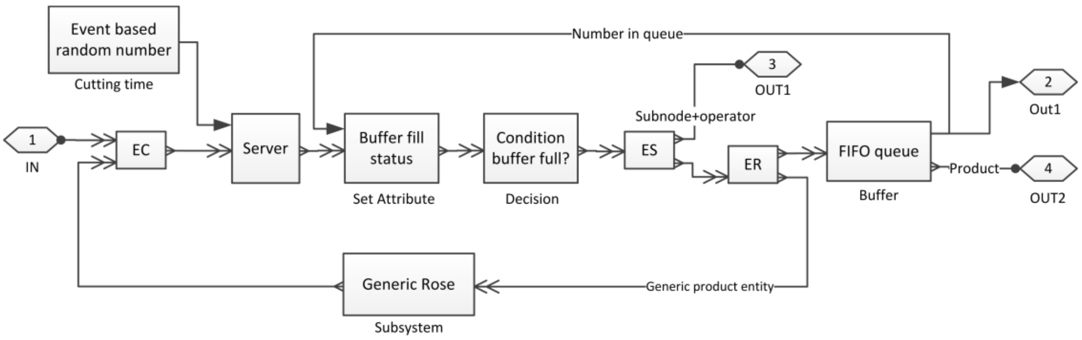
The subsystem *Perform task on Subnode* is detailed in Fig. 2.6b. The system element *2 Stage gutter speed select and set* in Fig. 2.6b is an optional, operator handled step control of gutter velocity u_G. It allows the operator to keep the gutter moving at a pre-selected constant velocity (*M*) or to stop it (*S*), when an action cannot be completed in time or is faster with a halted gutter. Per rose cut the operator has two decision moments just after and just before a rose cut. The algorithm selects the fastest 'move to rose' and 'cut rose' combination from four options: *MM, MS, SM, SS,* taking in account current status of the gutter, *M* or *S*, and the time needed to change gutter status T_{ts}. The model algorithm for operator movement is simple. During 'move to rose' the operator either walks at velocity v_o m s^{-1} in opposite direction of the gutter (*D+*), or at a higher velocity ($v_g + v_o$) m s^{-1} in the direction of the gutter movement (*D-*). During the action 'cut rose' the operator is assumed to stop walking ($v_o = 0$). In case, at $v_o = 0$, the gutter moves outside the reach of one arm length ($x_{tol} = 0.75$ m), the operator walks in direction *D-* during the cut action at velocity ($v_g + v_o$) m s^{-1}, with maximum speed, v_{o_max} =2 m s^{-1}. The decision for the fastest combination is based on an anticipated rose cut time T_{cr} of 3 s and a change status time T_{ts} of 2 s.



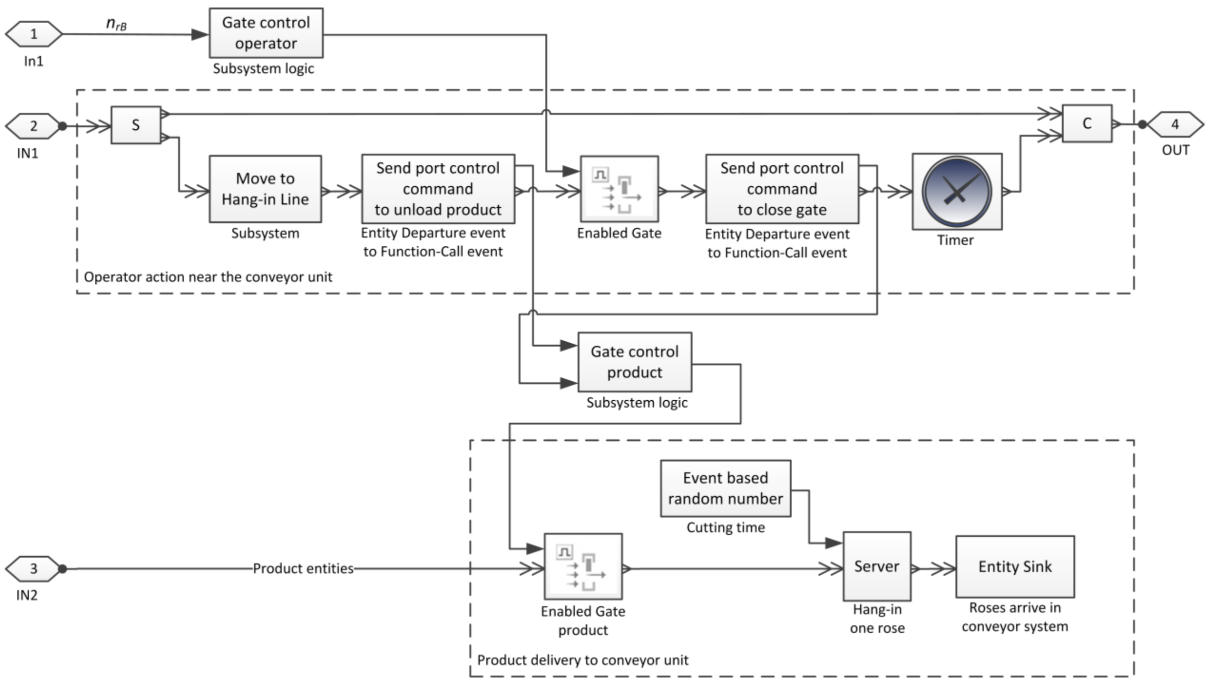
a) Subsystem *Process Subnode (Gutter)* in Fig. 2.5b



b) Subsystem *Perform Task on Subnode* in (a)



c) Subsystem *Cut Rose and place in buffer (on arm)* in (b).



d) Subsystem *Handle Product* in (a)

Fig. 2.6 - Nested subsystems to harvest rose stems from the gutter in the workspace (a), move to and cut a single rose (b), to actually cut a rose stem, generate a product-entity and buffer it in a queue (c), and to deliver a batch of roses one-by-one to the conveyor system (d). (⇉) entity path, (⟶) signal, C entity path combiner, S= output switch, EC=entity combiner, ES= entity splitter, ER= entity replicate.

In *Handle Product* (Fig. 2.6a), the hand-buffer is emptied by hanging the roses in conveyor units. Intermediate unloading of the hand buffer is performed when the buffer is full before a gutter is completely harvested. When the work on a gutter is completed, the gutter is sent away in *Send away subnode*. The element *Work in process* makes the operator-entity available. When both the operator-entity and the gutter-entity are available a new gutter is accepted for processing as a temporary combined entity. The element *Export operator attributes* accumulates and logs output attributes of the operator like raw process times $T_O(L,k)$ and walk distance D_o. In Fig. 2.6b the entity path indicates the harvesting of a single rose at a given position including calculation of gutter position $P_G(t)$ and harvester position $P_o(t)$ and control of the two-level gutter speed. The subsystem *Positions* uses service times and speed settings to determine the position of the gutter and the harvester. The loop repeats the process for each rose on the gutter. $P_G(t)$, $P_o(t)$ and gutter speed status v_{gS} may be logged for detail inspection of the process. The output ports OUT1 and OUT3 allow the worker-gutter-entity to leave the system when the gutter is completed or when the rose buffer is full. Fig. 2.6c shows the model for separating a rose stem from the plant. It generates single rose-entities, *product*, and stores these in a buffer represented by a queue. A counter on the number of rose-entities in the queue n_{rB} registers the status of the buffer. The subsystem *Handle Product* is detailed in Fig. 2.6d. It accepts the worker-entity and the rose-entities for placing the roses one-by-one in a conveyor unit. A gate is closed until the buffer is full or the gutter is completed. After acceptance by the conveyor unit the roses end in an entity sink, the system boundary of the model presented.

When a day-simulation is completed and all (or most) planned job-entities arrived at the JOB_OUT port (Fig. 2.4), the ready jobs, relevant attributes and variables in the system are exported for further processing, the daily feedback in Fig. 2.2. By doing so, the model is able to simulate a series of successive days.

2.3.4 Model implementation

The model was constructed in the Matlab environment using Simulink and SimEvents. SimEvents is a Matlab toolbox for discrete event modelling commonly used in studies on discrete event systems (Gray, 2007).

2.4 Materials and Methods

The model was tested and validated by means of data from a grower with a mobile rose production system. Company characteristics and data acquisition are described in Section 2.4.1. The methods used for model validation are given in Section 2.4.2.

2.4.1 Company characteristics and data acquisition

The grower produces rose cv. 'Dolomiti' on 3.8 ha equipped with twelve loops of 3120 m^2 each. Each loop consists of 284 movable gutters which circulate anti-clockwise according to Fig. 2.1. Allocated floor area per gutter is 10.4 m^2 (16 m * 0.65 m). In the workspace, gutters have seven adjustable velocities v_{gL} from 0.2 m s^{-1} to 2.0 m s^{-1} with steps of 0.3 m s^{-1}. An authorised worker pre-sets gutter speed v_g to match the number of harvestable roses in that loop. If the selected speed is too high, the worker stops and restarts the gutter by tapping a wire aligned to the work path. The worker has to tap and hold the speed control wire for 2s to send off a completed gutter to the end of the work path with a speed of 2 m s^{-1}. An automated gutter exchange procedure follows. Minimum cycle time of a single loop is 1 h 10 min. In the main aisle, a rose conveyor system serves as a buffer and transport unit to deliver cut-roses into the post-harvest processing room for grading, bundling, packing and cooling.

All loops are harvested daily. A worker normally cuts 450-500 stems h^{-1}. Daily target raw process time for harvest is maximal 8h in order to have enough time for other processes. Each loop is normally harvested by one worker. A second worker may assist for a number of gutters to finish in time. Workers buffer up to 25 roses in one hand (C_{hb}=25 with C_{hbm}=2).

Data for a full production year, 2009 were acquired. The daily number of harvested roses and the cycle time of each loop were recorded by the standard labour registration system PrivAssist® of the grower. The other tasks were recorded manually only and registered by the grower as weekly data. The composition of the used data is given in Table 2.1.

Table 2.1 - Data acquired at grower location with a) the labour registration system PrivAssist® for all loops in 2009 (all year), and October 18-22, 2010; b) video recordings at loop 7 on October 18-22, 2010. The columns S and P indicate the matching model symbol and purpose of acquisition.

Labour registration system	S	P	Video at loop 7	S	P
PrivAssist® (daily per loop):			Recordings harvest, disbudding, bending:		
• Yield (stems and stems m^{-2})	Y_L	(i)	Data acquisition probabilistic parameters:		
• Process time loop (h.mm)	T_0	(v)	• Cut rose (s)	$p_V(T_{cr})$	(i)
• Harvest capacity (stems h^{-1})	TH	(v)	• Hang in rose in conveyor system (s)	$p_V(T_{pd})$	(i)
Manual registration (weekly):			• Exchange gutter (s)	$p_V(T_{ge})$	(i)
• Yield per loop (stems)	Y_L	(c)	• Tap string (start/stop gutter) (s)	$p_V(T_{ts})$	(i)
• Labour time (h)	T_T	(v)	• Tap string (send away gutter) (s)	$p_V(T_{tl})$	(i)
			• Number of ripe roses per gutter (-)	$p_V(n_{r,L,G})$	(v)
			• Gutter speed level (m s^{-1})	v_g	(v)
			• Average operator speed (m s^{-1})	v_o	(v)
			Data acquisition performance:		
			• Cycle time gutter (harvest) (s)	CT_G	(v)
			• Interval time rose cutting (s)	-	(v)

Purposes: (i) data used to generate model input; (v) data used for model validation; (c) cross check

In addition, during 5 days October 18-22, 2010, harvesting was recorded on video at loop 7. Two Sony DCR-SR78E cameras were used to record the actions of workers and systems. The videos were processed with the behavioural research software, Noldus Observer XT. In Observer XT people and machines and behavioural actions of interest are defined and logged as events in the timeline of the observed video. The acquired data are listed in Table 2.1. Three, 35 min videos on harvesting by one operator, recorded on different days (2010, October 19th, 20th and 22nd), were used for estimation of the model parameters v_o, v_g, T_{ge}, T_{cr}, T_{ts}, T_{tl}, and T_{pd}. Gutter speed was measured from the distance between two reference points on the conveyor belt and the video recorded time the gutter needed to move between these points. The same method was used to estimate operator speed in normal walk direction (D+). No additional calibration was performed.

2.4.2 Model validation

Service station 1 ‘harvest’ (Fig. 2.3) was validated at different time scales (day, month). The standard model inputs stated in Table 2.1 and Fig. 2.2 were used. For the one day validation, the harvest of a complete loop was recorded on video on October 20th, 2010, 348 min in total. The video recordings were used for validation on the time performance of the model at node (loop) and subnode (gutter) level. The raw process time of the loop, the gutter cycle time and total labour time of the measured and simulated process were compared. It should be noted that 35 min of video on October 20th were also used for parameterisation of the model. As this amounts to 10% of the total video data used for model validation, it was considered to be a valuable, yet not fully independent validation. Therefore, the model was also validated for a longer period of one month using data that were acquired independent of the parameterisation data. During the one day validation, the harvest was partly done by 1 ($n_{G,1o}$=68) and partly by 2 operators ($n_{G,2o}$=216). Simulation results are averages of ten model runs to level out probabilistic effects. The validation for one month, October 2009, was done using PrivAssist® data on loop 7 only and simulations were not repeated. No video recordings were available for that month. The daily effective harvest rate in simulation and measured data were compared.

2.5 Results

2.5.1 Measured crop handling data, model parameterisation

The total working hours in 2009 for all main crop handling processes are given in Table 2.2. The average time for producing a single rose is 17.8s and average harvest time, the focus in this paper, is 7.7s. The number of workers in the greenhouse during harvest was on average 13.5, ranging from 10 to 17. Harvest (44%) and sorting (24%) represent the largest fraction of total labour time, followed by disbudding (17%), bending, cutting out of bad flowers, and cleaning respectively.

Table 2.2 - Total working hours and rose production in the mobile production system in 2009.

Task	Time (h)	%
Harvest	35,195	44.3
Sorting	18,951	23.9
Disbudding	13,476	17.0
Bending	6,726	8.5
Cut out	3,104	3.9
Cleaning	1,914	2.4
Total time	79,366	100
Total rose (stems)	$16 \cdot 10^6$	

The mean of the measured daily rose yield per loop was 1.11 stems m^{-2} (n=4068). The lower and upper 2.5% percentiles were 0.3 and 2.4 stems m^{-2}.

The parameters for the probability density function of the number of roses per gutter were determined from video recordings. On 50 evaluated gutters the mean number of roses per gutter was 17.3, with standard deviation 4.6. Based on this, in the model the coefficient of variation for the number of roses per gutter was set to 0.25.

As a result from video processing the probability density function of basic actions of the harvest process were determined. The resulting distributions and their parameters are given in Table 2.3. The probability density function for cutting a single rose is illustrated in Fig. 2.7, the distribution parameters in Table 2.3. The process time to cut a rose is well represented by a lognormal distribution (RMSD=0.05, r=0.97). Operator and gutter speed were estimated from the video recordings to be 0.1 and 0.2 m s^{-1}.

Table 2.3 - Parameters of probability density functions (pdf) for basic actions of the harvest process. The number of observations (*n*) is given and parameters p_1 and p_2. For a normal distribution, p_1 is mean and p_2 is standard deviation, and for a lognormal distribution, p_1 is μ and p_2 is σ.

Basic action time (s)	Symbol	pdf type	*n*	p_1	p_2
Gutter exchange time	$P_v(T_{ge})$	Normal	51	5.66	0.236
Cut rose	$P_v(T_{cr})$	Lognormal	916	0.237	0.545
Tap string short	$P_v(T_{ts})$	Normal	47	0.307	0.246
Tap string long	$P_v(T_{tl})$	Normal	8	1.65	0.4
Hang-in time	$P_v(T_{pd})$	Lognormal	973	-0.0074	0.625

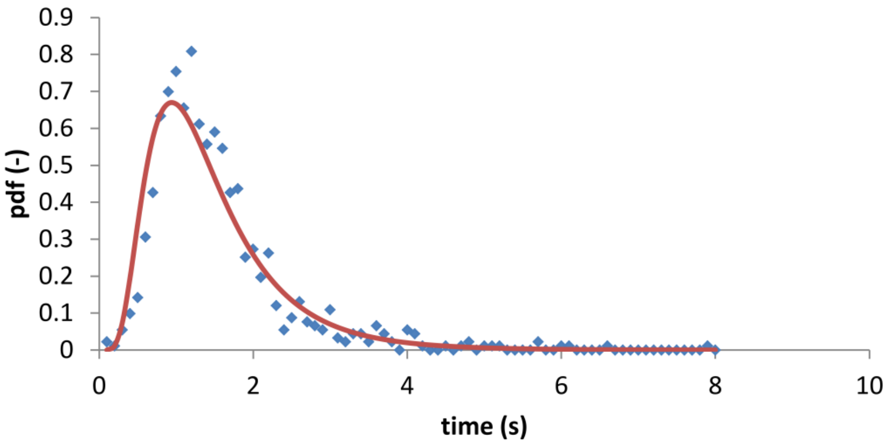


Fig. 2.7 - Measured frequency distribution (points) and lognormal probability density function (line) for net time to cut a rose (n=916, r=0.97).

2.5.2 Validation of the GWorkS model

Model validation at two levels is presented. First, model data was compared to data extracted from a video recording for one day. The second validation was done for a longer simulation period of one month. For the one day validation, the measured system performance and simulation results are presented in Table 2.4. The model accuracy in total labour time and raw loop process time is close to 95%. Total labour hours was 5.8% less in the simulation. The accuracy in the mean gutter cycle time is slightly less (deviation of 7%). Gutter cycle time in the 1 operator subsystem is 6.8% slower and in the 2 operator subsystem 6.5% faster than measured. The accuracy in gutter cycle time standard deviation (70%), shows that the model has a lack of correlation with respect to variation between gutters. Reality shows stronger stochastic effects than the model.

Table 2.4 - Model validation results for 20-10-2010, harvest of a full loop partly with 1 operator and partly with 2 operators. Comparison of main performance parameters of the harvest process at loop 7 according to 10 simulation runs and to measured data.

System Performance	Measurement	Simulation (10 runs) mean	std.	Accuracy %
Yield (roses)	4697	4683	(43)	99.7
Loop cycle time harvest	5:35:29	5:18:40	(0:02:12)	95.0
Total labour time	9:22:32	8:49:55	(0:03:05)	94.2
Gutter cycle time (1 operator)	n[a)]=68	n=65		
mean (s)	93.3	99.6	(1.9)	106.8
std. (s)	19.6	14.6	(2.4)	74.3
Gutter cycle time (2 operators)	n=216	n=219		
mean (s)	61.8	57.7	(0.4)	93.5
std. (s)	10.8	7.8	(0.4)	72.0

[a)] n is number of gutters processed in category.

Although from the video it is known how many gutters were handled by 1 or by 2 operators, in the simulation this is calculated by setting a target loop cycle time of 5:75h and an individual harvest rate of 500 stems h^{-1} because normally this is not recorded by the labour registration system.

For the second validation on the month October 2009, parameters in Table 2.3 were used and yield data ranged from 0.55 to 1.55 stems m^{-2} with average of 1.06 stems m^{-2}. In simulation, operator speed v_o was set to 0.1 m s^{-1} and gutter speed v_g to 0.2 m s^{-1}, no gutter speed control was applied. The fraction of the loop that was harvested with one operator was decided by the Job Planner (Fig. 2.2) based on an assumed individual harvest rate of 500 stems h^{-1} and target loop cycle time of 5:75h as in the one day validation.

Daily simulated and measured effective harvest rate in loop 7 *TH*(7,1) are depicted in Fig. 2.8.

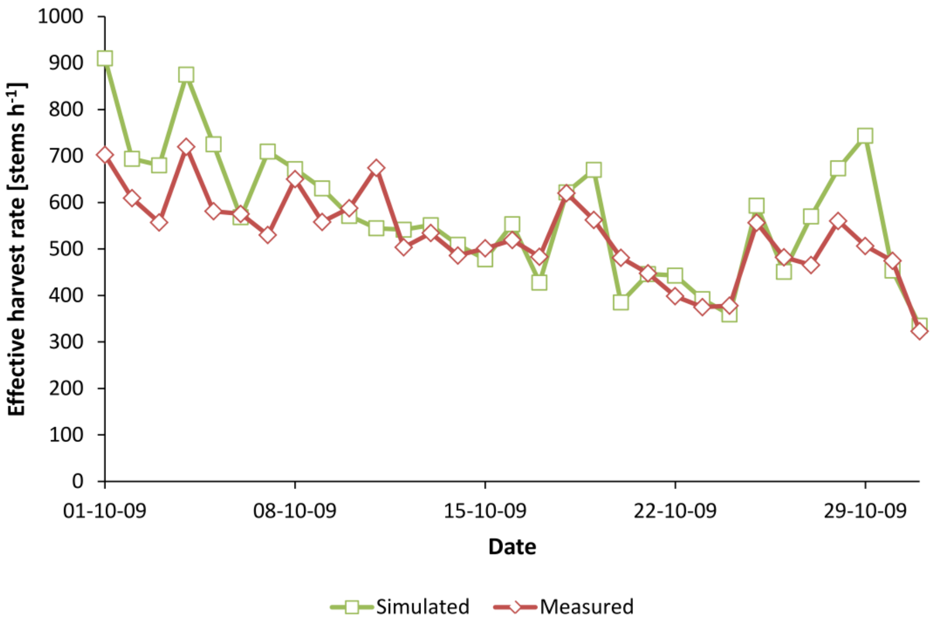


Fig. 2.8 - Model validation results for October 2009: Effective harvest capacity as ratio of stems harvested and loop cycle time.

The measured average harvest time per rose was 7.4s. In the simulation this was 7.6s. Average daily harvest rate accuracy was 92% with standard deviation 12.0%. RRMSE between measured and simulated harvest rate is 17.9%. RRMSE may be explained from the squared difference of the means SB (22%), the squared distance between standard deviations SDSD (26%) and the lack of correlation LCS (52%) between measured and simulated harvest rate. These results show that level and trend of the measured and simulated effective harvest rate are comparable and that lack of correlation between measured and simulated data is the main cause of deviation. Daily relative differences between measured and simulated data in effective harvest rate range from -20% to +47%. These differences and high LCS result from the fact that data on the fraction of the loop harvested by one operator and data on gutter speed level were not available. In case the model assigns more gutters to 2 operators than was done in practise, this leads to underestimation of raw loop process time and an overestimation of the effective harvest rate. The differences are thus explained from management differences between practise and model. Considering this and having the goal of designing automated production systems, the observed differences are acceptable.

2.5.3 System analysis: added value of the model

In this Section an illustrative application of the model is shown. For loop 7, it demonstrates respectively the effects of operator speed v_o and gutter speed v_g, and of yield Y_7 and gutter speed on the raw loop process time $T_0(7,1)$ with one operator harvesting. The operator speed and gutter speed were explored in the practical ranges [0:1] and [0.2:1.2] m s^{-1} respectively, with step size 0.05 m s^{-1}. Gutter speed control as described in Section 2.3.3.4 was applied allowing the operator to stop the gutter. The result is given in Fig. 2.9.

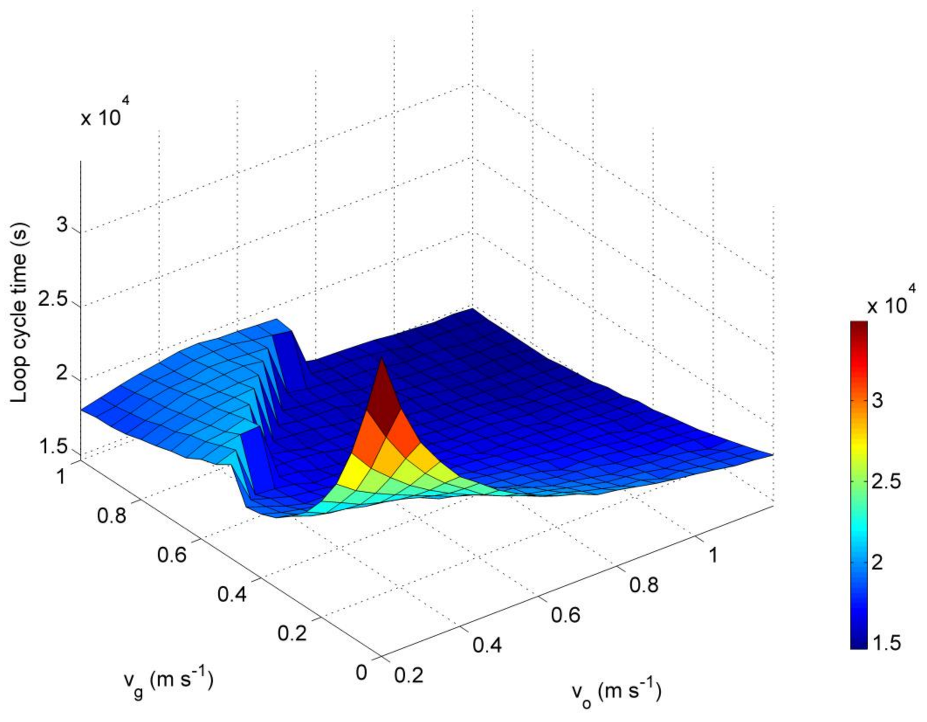


Fig. 2.9 - Raw loop process time $T_0(7,1)$ as a function of operator speed v_o and gutter speed v_g for yield Y_7 1.1 stems per m^2. Roses are harvested by one worker. (vector operator speed V_o=[v_o 1 2]; vector gutter speed V_g= [0 v_g 2]).

The raw loop process time for harvest $T_0(7,1)$ ranges from $14.7 \cdot 10^3$ to $34.9 \cdot 10^3$ s. Minimum $T_0(7,1)$ is found at maximum v_g and v_o. The steepest slopes occur at low values for v_g and v_o. At gutter and operator speed of 0.2 m s^{-1}, the slope in gutter speed direction is steeper, so it seems favourable to increase v_g instead of v_o. At low speed, the operator stops during a cut action and the gutter keeps moving, thus speeding up the whole process more. If, during a cut action, the gutter moves more than x_{tol} m, the operator also has to move to prevent the rose from moving out of reach. This does not affect $T_0(7,1)$. A slow operator and a fast gutter (Δv > 0.25 m s^{-1}) triggers the speed control algorithm to stop the gutter during cut actions. Despite the faster gutter during 'move to rose', this results in a sudden increase of $T_0(7,1)$ as is clearly visible as the ramp in Fig. 2.9. If v_g increases further at the same v_o, $T_0(7,1)$ will decrease only slightly since the 'move to rose' action decreases further. At high v_g and increasing low v_o, $T_0(7,1)$ increases slightly as well. This results from speed control which decreases gutter mobility. Speed control requires the operator to act by tapping a string, which takes on average 0.3s and forces the operator to stop. At increasing v_o, the gain from stopping the gutter will be smaller, thus resulting in increasing $T_0(7,1)$. Beyond a critical operator speed at $\Delta v < 0.25$ m s^{-1} there is no need to stop the gutter. This results in a decrease of $T_0(7,1)$ at $v_o > v_g - 0.25$ m s^{-1}. At higher speeds it is very likely that the operator loses control and $p_V(T_{cr})$ is no longer accurate. Thus in practice operator speed is limited to fit the operator skills. Under practical conditions with a yield of 1.1 stems m^{-2}, v_o is normally 0.2 m s^{-1}. At v_o=0.2 m s^{-1} the optimal gutter speed is 0.5 m s^{-1}. The data show for each operator speed an optimum gutter speed. So, the model can be used to find the best gutter speed for individual operators.

The parameters Y_7 and v_g were explored in the ranges [0.3:3] stems per m^2 and [0:1.35] m s^{-1} respectively, with step sizes 0.1 stems m^{-2} and 0.05 m s^{-1}. v_o was set to 0.2 m s^{-1}. Gutter speed control as described in Section 2.3.3.4 was applied. The result is given in Fig. 2.10.

The main effect is that raw loop process time $T_0(7,1)$ increases almost linearly with yield. At high gutter speed, the $T_0(7,1)$ is generally less than at low gutter speed. In gutter velocity range 0-0.45 m s^{-1}, the solution plane curves more and shows a minimum. At gutter velocity 0 m s^{-1} progress fully depends on operator speed. From 0 m s^{-1} onward, the process takes advantage of an increase in gutter speed, since transport times decrease during both basic actions, 'move to rose' and 'cut rose'. At $v_g > 0.45$ m s^{-1} and $\Delta v > 0.25$ m s^{-1} halting of the gutter during cut actions results and the positive effect of v_g during rose cutting is lost. At a low yield minimum $T_0(7,1)$ occurs at 0.45 m s^{-1}. At $v_g > 0.45$ m s^{-1} and low yield a small increase in $T_0(7,1)$ occurs since the operator has to tap the string at each rose position. For a yield of 2.9 stems m^{-2} a minimum value occurs at 0.25 m s^{-1} gutter speed. Above this speed, the increase in $T_0(7,1)$ is caused by the fact that the gutter reaches its end position and stops before harvest is completed. This slows down the process 'move to rose' on a section of the gutter. With decreasing yield, the operator has to handle less gutter length after the gutter reached its end point. These results show that model calculations help to find the optimum gutter speed for every yield.

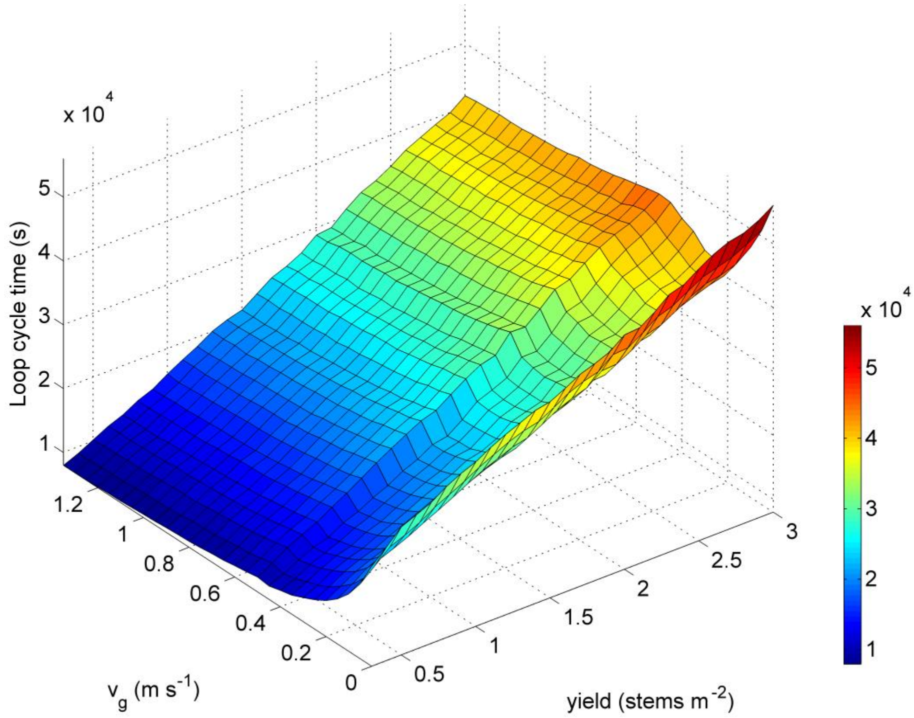


Fig. 2.10 - Raw loop process time $T_0(7,1)$ as a function of yield Y_7 and gutter speed v_g for operator speed v_o= 0.2 m s^{-1}.

2.6 Discussion

The model is able to explore parameter sensitivity in a large field of parameter values as shown in Fig. 2.9, however the model cannot predict when the system is moving so fast that hand eye coordination of the operator will fail. Practise shows that high gutter speed is only applied at low yield Y_L. The model ensures harvest of all ripe roses using the probability density function in Fig. 2.7. The operator stops the gutter when it moves too fast, or cuts the last roses when the gutter has reached the end point.

The model is able to define processes at the level of detail needed. A service station as defined in Fig. 2.3 may be anything between a *server* and a detailed multi-layer *subsystem* that models the process to the detail needed for testing new implements in a growing system. In the current model the harvesting *subsystem* is detailed enough to allow that the human harvester is replaced by a robot. To be effective in optimizing the use of automation in greenhouses, it is necessary to replace the system elements that describe the harvester with elements that describe the function of the automation itself. The focus of this research was simulation of a current man operated system to create a reference and to determine the performance quality of the model.

For now crop production and the need for crop handling actions are measured inputs to allow validation of the GWorkS model. In future, crop growth and production models combined with climate models may be used to test different scenarios in the operation of (new) growing systems. The structure and setup of the GWorkS model is kept generic where possible and is made specific for the mobile rose growing system where needed. This approach enhances model flexibility and applicability in other growing systems.

2.7 Conclusion

Crop handling processes inside greenhouses with a mobile crop production are adequately captured in a discrete event system model with probabilistic parameters for basic man driven actions and deterministic mechanisms for required movements of people and installations. Results of a single day validation show that the model estimates harvest labour time with an accuracy of 94%. For a one month validation an accuracy of 92% and RRMSE of 18% resulted. The value of RRMSE was caused by missing data on the number of workers at the loop and on the actual gutter speed level. The model validations show good quality of the results. The model exposes effects of the internal parameters that are not immediately available from acquired data and it can determine best system settings as is illustrated for operator and gutter speed settings at given rose yield levels. Advantages of the model are: 1) better decisions in assessing engineering solutions, 2) the model enables us to look into complex crop handling processes in greenhouses and 3) the model allows us to optimise systems, ranging from system design to determining best values for system parameters. Drawbacks of the model are: 1) effort is needed to create a reliable model, 2) a generic model structure is necessary to allow system flexibility, and 3) possible inaccuracy of the model when it is used in newly designed growing systems. For the GWorkS model, it is concluded that it can be used for studies on design and management of mobile rose growing systems and that it has system flexibility as a result of its generic system hierarchical structure and its generic approach to crop handling processes.

2.8 Acknowledgements

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Chapter 3

Simulation of harvest operations in a static rose cultivation system

A. van 't Ooster, J. Bontsema, E.J. van Henten, S. Hemming

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3 Simulation of harvest operations in a static rose cultivation system

3.1 Abstract

Labour is the most dominant cost factor in Dutch cut-rose production. To improve crop production systems and labour management, a generic process modelling approach was developed enabling the impact of different scenarios for their impact on labour productivity to be assessed. The crop production system with crop handling processes is defined as a stochastic discrete event system. This paper demonstrates the model flexibility and transferability by adapting an existing model developed for a mobile rose production system to a model for a static growing system for cut roses. The paper describes the adaption process. The adapted model was validated for the harvest process at a 3.6 ha production site in the Netherlands. Work scenarios were simulated to examine effects of skill, equipment, and harvest management.

The model reproduces the harvest process accurately. A seven workday validation for an average skilled harvester showed a relative root mean squared error (RRMSE) under 5% for both labour time and harvest rate. A validation on 96 days for various harvesters showed a higher RRMSE, 15.2% and 13.6% for labour time and harvest rate respectively, mainly caused by the absence of model parameters for individual harvesters. The model was successfully used in scenario studies and indicated that worker skill as an important cost factor, differences of harvest trolley type are small, and that an extra harvest cycle per day is only feasible when compensated by product price. Overall, the generic model concept performs well for a static growing system when extended with system specific properties and process elements.

Nomenclature

C_o	Individual harvest rate of an operator (stems h^{-1})
C_T	Mode of load capacity of trolley buffer in units of product
C_{Tm}	Tolerance buffer capacity on trolley in units of product
CT_n	Cycle time of node *n* (s)
CT_{sn}	Cycle time of subnode *sn* (s)
d_{hc}	Decision parameter, allowed number of harvest cycles ($d_{hc} \in [1,2]$)
d_U	Decision parameter, abandon harvest operation in path to unload rose nets
d_{Un}	Decision parameter, number of rose nets to unload from trolley to buffer in main aisle [U_n=0,1,2]
D_o	Overlap distance between a move action and a basic action at a place of action (m)
$D_T(n,k)$	Cumulative travel distance of operator since t_0 within task *k* in node *n* (m)
$E(\nu)$	Expectation of stochastic variable ν
GWorkS	Greenhouse Work Simulation, an acronym used as the model name
LCS	Lack of correlation, weighted by the standard deviations
MSD	Mean square deviation
n_{hc}	Number of harvest cycles per day
$n_{r,n,sn}$	Stochastic variable number of ripe stems per subnode *sn* in node *n*
$n_{rnd}(i)$	Units of product in delivered rose net *i*
$N_{rnd}(n)$	Number of rose nets delivered in node *n*
r	Correlation coefficient
$P_{r,n,sn}$	Stochastic variable position of ripe stems per subnode *sn* in node *n*
RRMSE	Relative root mean squared error
SB	Squared bias, squared difference of means
SD	Standard deviation
SDSD	Squared difference between standard deviations
t	Simulation time (s)
t_0, t_f	Start and end time of simulation (s)
$t_{0,2}(d)$	Measured start time 2nd harvest cycle on date *d* (s)
$T_{0,rn}(i)$	Raw process time of rose net *i* (s)
T_{bb}	Stochastic variable service time to bind a rose net to a bundle (s)
T_{cr}	Stochastic variable service time to cut a single rose (s)
T_o	Stochastic variable overlap time between two basic actions (s)
T_{p1n}, T_{p2n}	Stochastic variable service time to place one, two empty rose nets in the trolley (s)
T_{pb}	Stochastic variable service time of a push impulse to a manually driven trolley (s)
T_{stb}	Stochastic variable service time to place a single rose in the trolley buffer (s)
T_{t1n}, T_{t2n}	Stochastic variable service time to log one or two empty rose nets in the labour registration system (s)
$T_T(n,k)$	Total labour time on task *k* in node *n* (s)
$T_{Tc}(n,k)$	Total pure cut time within harvest task in node *n* (s)
$T_{To}(n,k)$	Total overlap time between two basic actions within task *k* in node *n* (s)
$T_{Tr}(n,k)$	Total handling time of rose nets harvest task in node *n* (s)
$T_{Tt}(n,k)$	Total transport or move time within task *k* in node *n* (s)
$T_{Tw}(n,k)$	Total wait time within task *k* in node *n* (s)
$V(\nu)$	Variance of stochastic variable ν
v_o	Operator velocity at task execution (m s^{-1})
$Y(d,n)$	Measured daily yield in node *n* on date *d* (stems m^{-2})
$Y_2(d,n)$	Measured daily yield 2nd harvest cycle in node *n* on date *d* (stems m^{-2})
Y_n	Daily yield per node *n* in units of product
$\overline{y}$	Mean of measured data
μ	mean of the variable's natural logarithm for pdf-type LN(μ,σ^2) or the variable itself for pdf-type N(μ,σ^2)
σ	standard deviation of the variable's natural logarithm for LN(μ,σ^2) or the variable itself for N(μ,σ^2)

3.2 Introduction

Systematic and quantitative methods to analyse, simulate and optimize the production process in greenhouse horticulture and to support decisions in this field are hardly available (Montero, Van Henten, Son, & Castilla, 2011). The perspectives of such methods are reduction of trial and error in crop production system design for an optimal labour process and quantitative evaluation of new scenarios in crop handling processes. Only few examples of research in this field have been described (Fang, Ting, & Giacomelli, 1990; Bechar, Yosef, Netanyahu, & Edan, 2007; Bechar, Lanir, Ruhrberg, & Edan, 2009; Van 't Ooster, Bontsema, van Henten, & Hemming, 2012). A generic modelling and simulation instrument for systematic evaluation of greenhouse crop production systems is required for production process improvement and decision support in current Dutch greenhouse horticulture.

Van ’t Ooster et al. (2012) presented the framework of the Greenhouse Work Simulation (GWorkS)-rose model as a simulation tool for crop handling processes in a mobile growing system for cut rose and a validation of its performance in the harvest process. This paper presents a second step in the development and application of the new model. The first objective of this research is to prove that the GWorkS-rose model has a generic and flexible modelling approach, and that it is able to simulate the harvest process in a static cut-rose production system with limited modification. To demonstrate this approach, the subject of study was changed from a mobile system where operators work at a specific area in the main aisle to a system where roses were grown in static gutters and operators work in paths beside the roses. This static growing system required adjustments to the model in the description of the flow of the operations. New model elements were developed (Section 3.3.4). The quality of the model for the static growing system is proven (Section 3.5.2).

The second objective was to test the model accuracy and to explore its quality as a tool for scenario assessment. This provides a new tool to assess performance of equipment (electric trolleys) and of personnel for management decisions and improved labour productivity (Section 3.5.3). The paper finds answers to questions concerning the management and the organisation of the work in the greenhouse, as well as the influence of operator skill on the labour time and harvesting cost.

3.3 GWorkS-rose model for a static rose growing system

The model, GWorkS-rose, is a stochastic discrete event simulation model of crop handling processes and logistics inside a greenhouse for cut-rose production. The model is a generic simulation environment for assessment of labour management, work-scenarios and evaluation of crop production systems. The basic model formalism and model structure are described in Van 't Ooster et al. (2012). The focus in this paper is on flexibility of the model with respect to system modification as is proven by extension to a static rose growing system and by evaluating the model for its performance in this system. Furthermore, the model was applied to assess different scenarios to prove its value for evaluating management decisions.

3.3.1 Production system

In a static rose cultivation system in a greenhouse in The Netherlands, roses are grown on substrate filled gutters with a closed irrigation system. Plant density is around 6 plants m^{-2}. The static gutters are positioned at 0.5 to 1 m above floor level and stretch from a centred main aisle to one of the side walls. The crop system lay-out is outlined in Fig. 3.1. Groups of 4 gutters form a bed with a path at each side. Harvest is one-sided, so half of a rose bed of 2 gutters is harvested each passage along the path. Each greenhouse span has two paths. Greenhouse spans are grouped into a section to form a work unit for one harvester. In situations of high yield, a second harvester assists by harvesting some section paths. On days when roses are blooming rapidly, the grower may plan two harvest cycles on one day in order to harvest optimal flower quality.

Either electrically-driven trolleys are used to transport the harvester and to buffer the cut stems or hand-pushed trolleys are used to buffer stems. Both run along the so-called pipe rail system, which is also used as heating system. After cutting, the roses are placed in buffers at the front end of the trolley. These buffers are nets hanging in containers. An electrical trolley has a buffer at each end, with the harvester in the middle. The buffer in front of the harvester is filled. Occasionally, stems are moved from one buffer to the other. The buffer capacity of a trolley is well above 400 stems. At return to the main aisle the harvester decides to unload zero, one or two nets. This decision depends on the remaining buffer capacity and the expected yield in the next path. Only at completion of a section are nets unloaded to allow yield registration per section. A hand pushed trolley has one buffer with half the buffer capacity of an electric trolley. At the end of the path the buffer is rotated 180°. The number of roses per delivered net is flexible with average 150 and maximum 300 stems. Full rose nets are placed on water in transportable buffers on the main aisle with a capacity of up to 10 nets. At regular intervals these buffers are transported to the processing room where the roses are de-bundled, sorted, bundled for the market and packed.

The harvesters, greenhouse sections and rose nets all have an electronic tag for identification. A labour registration system with terminals in the greenhouse registers the tasks executed. The sorting machine in the processing room counts the number of roses per net.

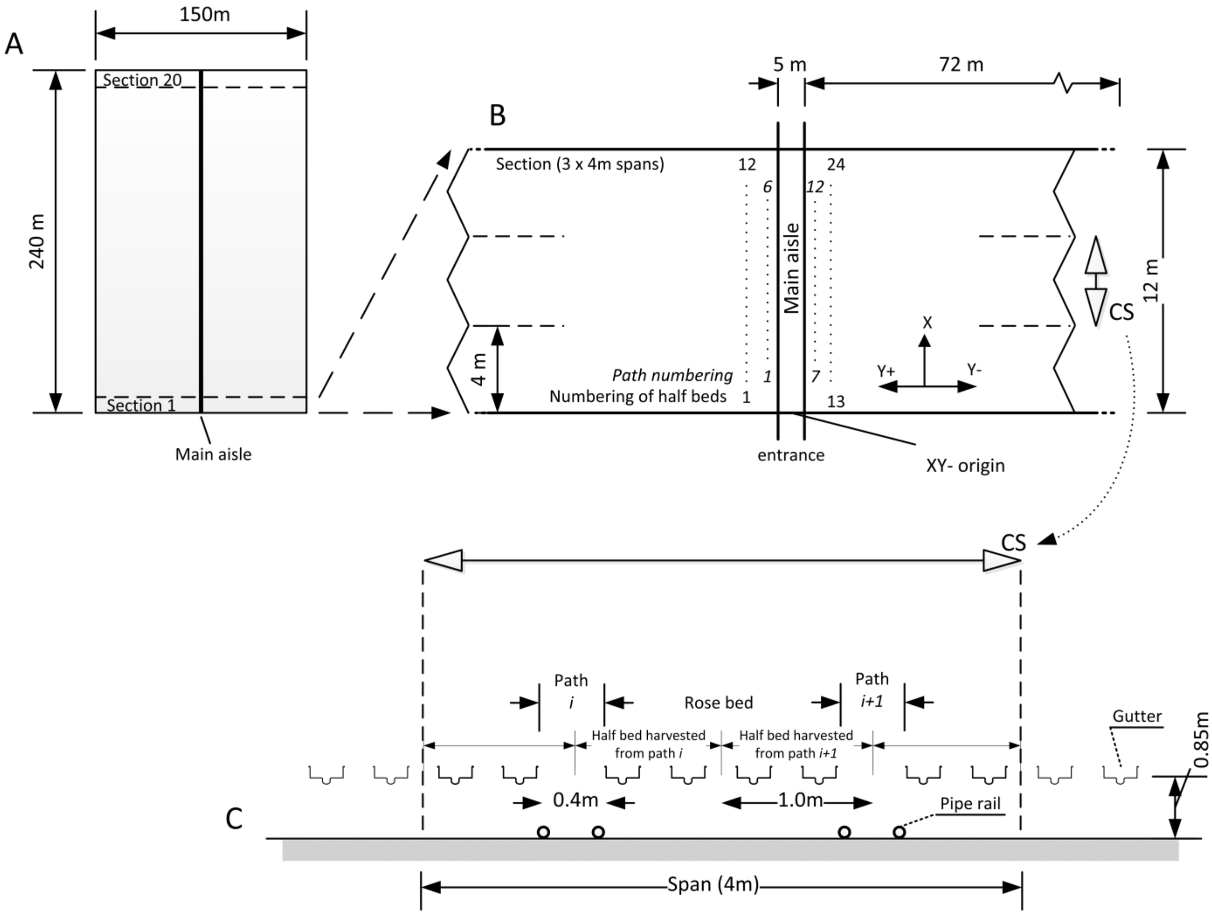

Fig. 3.1 - Layout and coordinate system of the cut-rose greenhouse with 20 sections of 3 spans each (A). Top view of section 1 with 24 rose beds and 12 paths (B), and a vertical cross sectional view of one span inside a section (C). The XY-origin is the main aisle mid at the entrance in section 1. A section includes both sides of the main aisle. The numbering of sections, rose-beds, and paths is given in (A) and (B). The cross sectional view shows the vertical dimensions, the pipe rail system, and the rose beds that consist of two gutters each.

3.3.2 Process model of the harvest operation in the Integrated DEFinition method for process description capture (IDEF3)

In a process analysis prior to implementation in GWorkS-rose, the work process flow diagram of the harvest process in a static growing system (Fig. 3.2) was developed using the IDEF3 modelling formalism scheme (Kusiak, Nick Larson, Wang, 1994) and verified in practice.

An IDEF3 process flow diagram outlines a sequence of activities or process steps within a given setting. It consists of units of behaviour (UOBs), links, and junction boxes. A UOB represents an activity or action occurring in the process. Examples of UOBs are ‘get trolley and equipment’ (2), ‘get rose nets’ (3), and ‘bind roses’ (18). Links represent relationships between UOBs. Junctions model the branching logic within a process. The branching logics are the logical *and (&)*, *or (O)*, and *exclusive or (X)*. The process paths converge (*fan-in*) or diverge (*fan-out*) at a junction. The symbols used in Fig. 3.2 are explained in Table 3.1.

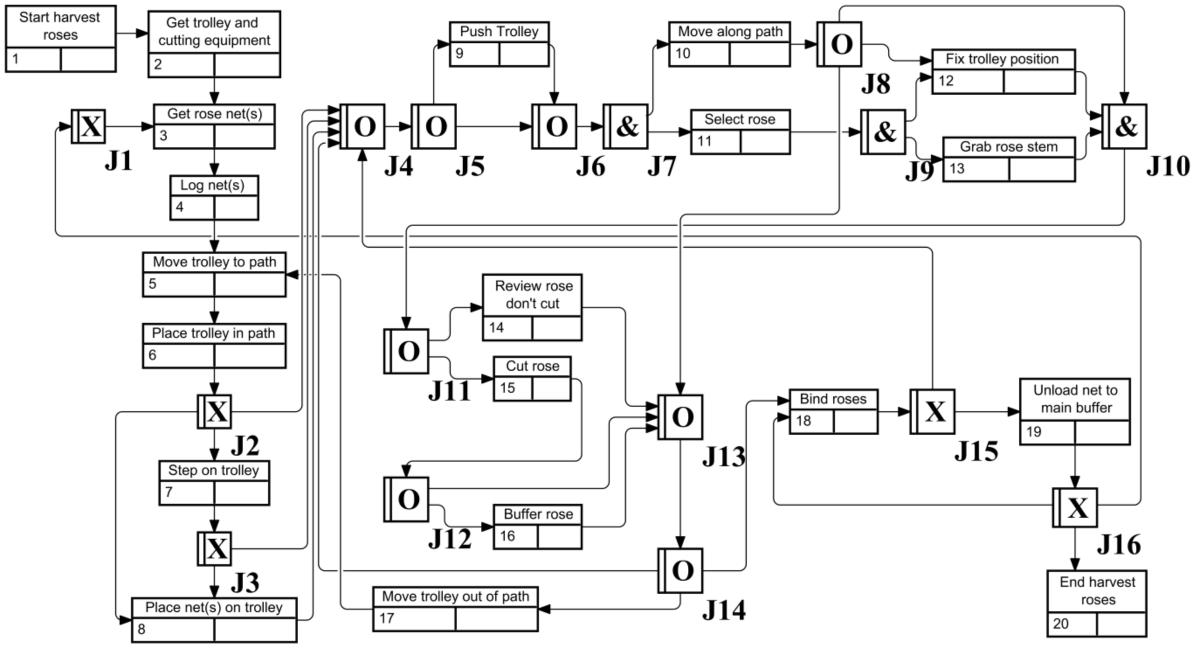

Fig. 3.2 - IDEF3 process flow diagram of the harvest operation for electric and hand pushed trolley.

The definition of actions in the harvesting process is explained for harvesting a single rose using an electric trolley. It starts with the action 'select rose' (11), then 'grab rose stem' (13), followed by the action 'cut rose' (15). In the action 'review rose, don't cut' (14) the rose is merely reviewed, not cut. 'Cut rose' starts when the harvester's hand holding the scissor starts the movement towards the stem to be cut and ends when the rose holding hand is back within the perimeter of the trolley. The action 'buffer rose' (16) refers to placing a stem in the trolley buffer. It starts at the end mark of the action 'cut rose' and ends when the hand releases the rose to the buffer. The action 'move along path' (10) and 'select rose' (11) are partly executed in parallel, as are the actions 'buffer rose' (16) and 'move along path' (10). The sequence of actions to cut a rose (11, 13 & 15) begins while the trolley is still moving, then the trolley stops at the rose position (12) and moves again when the action 'cut rose' is completed. The end of the harvest process (20) in the greenhouse is marked at the deposit of the filled rose nets in the water filled buffers (19) that complete a harvest cycle. Actions (1) - (8) are needed as preparation before entering a harvest section and as intermediate actions between paths. The action 'push trolley' (9) is specific for an hand pushed trolley.

3.3.3 Modelling formalism

The GWorkS-rose model (Van 't Ooster et al., 2012) describes process handling actions of humans and mechanised components as a stochastic discrete event system using queueing theory (Cassandras & Lafortune, 2010). The model structure and content is modular. The greenhouse and growing system are defined parametrically, e.g. greenhouse length, span width, and number of spans and greenhouse section size, rose bed width and path width.

Table 3.1 - Symbols used in IDEF3 process model.

Symbol	Short name	Description
UOB Labels Node Ref # | IDEF Ref #	Unit of behaviour (UOB)	Activity occurring in the process. The UOB label is a 'verb-phrase' identifying the activity. The lower left Node Ref # is a unique number. The lower right box is an optional reference (not used).
⟶	Simple precedence link	One of three types of links in IDEF3 expressing temporal constraints between UOBs.
X	Junction *exclusive OR*	Fan-in: exactly one preceding process completes Fan-out: exactly one following process starts
O	Junction *asynchronous OR*	Fan-in: one or more preceding processes must be complete Fan-out: one or more following processes must start
&	Junction *asynchronous AND*	Fan-in: all preceding processes must be complete Fan-out: all following processes must start

The model uses measured crop yield and it follows the system hierarchy by representing the greenhouse as a collection of exchangeable node models. A node model describes a single crop handling process like harvest in Fig. 3.2 at a major location in the greenhouse like a section in Fig. 3.1 by means of a network of queues, servers and logical operations. The job planner defines the daily workload in the greenhouse based on numbered jobs and job-frequency information. The job planner assigns nodes and subnodes to resources like operators with trolleys. Terms such as entity, job, node, subnode, resource and action represent the abstract level of the model, whereas terms like harvest, greenhouse section, rose bed, harvester, trolley, and 'bind roses' represent the physical system. The model has stochastic variables for the process times of elementary actions like cut a single rose (T_{cr}), as well as for distribution of ripe stems over rose beds to generate positions of ripe stems called *places of action*. Move actions are defined deterministically and calculated as the distance divided by operator or equipment speed. A detailed description of the model and its validation for harvest in a mobile crop production system is given in Van 't Ooster et al. (2012).

3.3.4 Specific model extensions

In order to simulate the static rose production system according to Fig. 3.2, the model functionality was extended. This was done by creating additional substitutable subsystems at several levels in the model system hierarchy, by modification of entity attribute lists, and finally by creation of alternative execution pathways in the model. This concerned the UOB's 2 - 9, 12, and 16 - 19 in Fig. 3.2.The most relevant model novelties are described in this section. The model was extended to allow object movement in an xy-coordinate system (Section 2.4.1), job frequencies higher than once a day (Section 2.4.2), parallel processing of tasks in different paths of one greenhouse section (Section 2.4.3), parallel actions like 'cut rose' or 'buffer rose' while 'moving along path' (Section 2.4.4), and operator decisions at path completion (Section 2.4.5).

3.3.4.1 Coordinate system and travel distance

In the static crop production system, operators and equipment (*resources*) move in the xy-grid indicated in Fig. 3.1. Coordinates of greenhouse sections (*nodes*), half rose beds (*subnodes*), and positions of ripe stems (*places of action*) are determined by the model based on dimension parameters of the greenhouse, the growing system and measured yield per node. Each service requesting object (*entity*) gets assigned the base coordinate of its position. Small entities like human operators are considered as point objects. For moving resources, the base coordinates are updated after each move action. A service time of a move action is calculated as the distance divided by operator or equipment speed. The distance between two actions results from the coordinates of the place of action and the position of the operator. The path travelled by the operator (e.g. harvester) is determined by the order of actions (Fig. 3.2), the positions of the necessary equipment (e.g. trolley, rose nets, and time-log points), the node to act in (greenhouse section), and a pre-set order of subnodes (rose beds) where roses are harvested. On the main aisle the shortest path between base coordinates is used. Movement in cultivation paths, along subnodes, is only in the y direction.

3.3.4.2 Job frequency

In rose cultivation, harvest is an everyday process for all nodes, a straightforward action for the existing job planner (Van 't Ooster et al., 2012). In the original model, this job planner was designed for a maximum job frequency of once a day. However, some growers with static crop systems occasionally harvest twice a day. To handle this 2nd harvest cycle, the decision parameter $d_{hc} \in [1,2]$, defining the allowed number of harvest cycles, was introduced together with measured yield data $Y_2(d, n)$ and start time $t_{0,2}(d)$ of the 2nd harvest cycle. If d_{hc}=2 and for date d and node n, $Y_2(d, n)$ > 0 stems m^{-2}, an additional harvest task is assigned to the job-entity.

3.3.4.3 Multiple operators in a node

When two operators work in one node (i.e. one greenhouse section), they harvest different paths using different trolleys. Each worker-trolley-combination is defined as a separate subsystem in the model. These subsystems in the model are equal, parallel-connected process models for harvesting a series of subnodes. This approach prevents process interference and interference of accumulators that register individual labour time and travelled distance. Job navigation through these subsystems requires separate job-entities to allow parallel operation. These additional job-entities are child entities derived from the parent job-entity. Assignment of subnodes to separate operators by the job planner triggers the generation of these child entities. Up to two additional harvest dedicated child entities may be generated, allowing parallel operation of 3 workers in one node.

3.3.4.4 Time overlap between actions

In practise a time overlap between the actions ‘cut rose’ and ‘move along path’, and ‘buffer rose’ and ‘move along path’ was found for harvesters working with electric trolleys. Partial parallel execution of actions was included in the model by introducing an overlap distance D_o for ‘cut rose’. At 0.5 m before arriving at the place of action, a skilled worker starts the cut action while still ‘moving along path’. For the actions ‘buffer rose’ and ‘move along path’ full parallel execution was introduced. Both parallel executions are constrained by the distance between ripe roses. For hand pushed trolleys, only the overlap between ‘cut rose’ and ‘move along path’ is relevant.

3.3.4.5 Operator decisions at path completion

With electric trolleys, operators decide after completion of a path, to unload one or two fully or partly filled rose nets to a water-filled buffer in the main aisle and to reload and time-log an equal number of new nets, or they decide to continue harvesting in the next path without emptying the trolley buffers. In the path, full nets lead to abandoning the harvest operation for unloading. A model decision tree for unloading rose nets has been defined. At each ‘cut rose’ action, the decision tree is updated. Outputs of the decision tree are, the unload decision at return to the main aisle $d_{Un} \in [0,1,2]$, and the decision for intermediate unloading d_U. If d_{Un}=1, the bundle with the highest fill status is unloaded and if d_{Un}=2 both nets are unloaded. The unload decision d_{Un} depends on fill status of the rose nets, expected number of stems in the next path, and task completion within a node. For a hand pushed trolley a more simple decision tree was defined with $d_{Un} \in [0,1]$. d_U is true if in a path the buffer reaches its capacity C_T and the remaining number of un-cut roses is greater than the buffer tolerance C_{Tm}. C_T is mode and C_{Tm} is 2.33*SD*, thus leaving about a 1% probability that a real rose net fill is outside this bound when a normal distribution of rose net fill status at delivery is assumed.

3.3.5 Model implementation

The GWorkS-model is implemented in Matlab® using Simulink and SimEvents. SimEvents is a Matlab toolbox for discrete event modelling commonly used in studies on discrete event systems. The graphical model implementation allows a clear system hierarchical representation of the system.

3.4 Materials and methods

The model was validated and used for a scenario study using data from a specific grower. Data acquisition is described in Section 3.4.1. Methods used for model calibration and validation are given in Section 3.4.2. The scenarios simulated to demonstrate value and flexibility of the model are described in Section 3.4.3.

3.4.1 Data acquisition

During the summer of 2011, yield and labour data were acquired daily in a 3.6 ha cut-rose producing greenhouse with a static rose growing system in the Netherlands (Van den Berg Roses). The grower uses electrical trolleys which are currently considered as most effective with respect to labour efficiency. To harvest optimal quality, one or two harvest cycles occurred on a day.

The labour data originate from the labour registration system Dytime®. The daily time line per worker, the number of harvested roses per rose net, the section where each rose net was harvested, harvester performance (number of stems cut, labour time, mean stem length, %-curved stems, %-shortened stems), and total harvest labour times were recorded. The daily yield per greenhouse section $Y(d,n)$ and $Y_2(d,n)$, the start time of the 2nd harvest cycle $t_{0,2}(d)$, and the process time per rose net $T_{0,rn}$ were derived from these data. $Y(d,n)$, $Y_2(d,n)$, and $t_{0,2}(d)$, are model inputs.

During 5 days in the period June 2nd to 15th, 2011, the harvesting process was video recorded on one of the trolleys. Two Sony DCR-SR78E cameras were used to record the actions of workers and the position in the greenhouse. The videos were processed with the behavioural research software, Noldus Observer XT®. In Observer XT, actions of interest of people and equipment are logged as events in the timeline of the observed video. An event either defines a time interval per single action for actions of interest, or it is used as a point in time for counting or marking purposes like start/end of path, rose cut, and rose arrival in buffer. One complete first harvest cycle was used for estimation of the model input parameters, mean operator speed in path v_o, time to cut a single rose T_{cr}, time to place a harvested rose in the buffer T_{stb}, time to bind a rose net to a bundle T_{bb}, times to log one or two rose nets T_{t1n} and T_{t2n}, and times to place one or two empty rose nets in the trolley T_{p1n}, T_{p2n}. T_{bb}, T_{t1n}, T_{t2n}, T_{p1n}, and T_{p2n} are elementary action times within the process of unloading rose nets to the main buffer. Next to that the overlap time of actions 'move along path', and 'cut rose' T_o was recorded. Overlap times between two actions as revealed in video recordings were determined using a visual basic algorithm.

3.4.2 Model calibration and validation

The model was calibrated for one full harvest cycle in greenhouse section 2 (1800 m^2) based on video recorded harvest performance of an average harvester, identified as harvester 34, with a mean harvest rate C_o of 528 stems h^{-1}, measured over 33 available harvest cycles. The video recording took place on June 15th, 2011. Video results matched with labour registration data with respect to labour time and number of roses harvested. From the measured data, breaks of harvesters were excluded, since the model does not include breaks. As the model has stochastic elements for process times of elementary actions (T_{cr}, T_{stb}, T_{bb}, T_{t1n}, T_{t2n}, T_{p1n}, and T_{p2n}), as well as for locating ripe stems along paths ($n_{r,n,sn}$, $P_{r,n,sn}$), a test was made of how the number of runs affected the averaged output. It was observed that deviation of average section cycle time after 4 and 10 run repetitions was close to 1%. The cause of this small change is that stochastic processes occur at the level of single actions of the harvester and not at the level of accumulated daily results. During a simulation of one day the probability density functions are sampled 24 to 8000 times. This high number of samples has a smoothing effect on the result. Therefore, a low number of run repetitions is sufficient for presentation of the average. For calibration the results of 10 simulation runs were averaged.

The video data showed considerable variance in the time needed for basic actions. Table 3.2 presents the probability density functions (pdf) for basic actions that were assumed stochastic, with pdf-type and parameters as determined from the video recordings. Histograms and Q-Q plots were used on observed data and on the natural logarithm of observed data to find the best pdf-type and Matlab® was used to estimate distribution parameters from the data.

Trolley speed was determined from video recordings as the ratio between path length and total time the trolley 'moves along path' at each rose bed. Trolley cruise speed over longer distances was 1 m s^{-1}. The actual mean trolley speed v_o in greenhouse section 2 was 0.39 m s^{-1}, with standard deviation 0.08 m s^{-1} (n=24). In the model, trolley speed between two cut actions was assumed constant at 0.39 m s^{-1} except for very low yield (< 0.28 stem m^{-2}) where trolley cruise speed was assumed. For operator movement outside the trolley, a constant walking speed of 1.5 m s^{-1} was used.

Table 3.2 - Probability density function (pdf) type and parameters that define stochastic process times of basic actions in the harvesting process of roses as determined from video recordings. Harvest cycle June 15th, 2011 (7:45-11:00 h), Harvester 34, n is number of observations, μ and σ are the mean and standard deviation of the variable's natural logarithm (lognormal) or of the variable itself (normal).

Basic action	Symbol	pdf type	μ	σ	n
Cut rose	T_{cr}	lognormal	1.305	0.361	1517
Buffer rose	T_{stb}	lognormal	-0.396	0.662	497
Bind roses in net	T_{bb}	lognormal	2.900	0.349	35
Place 1 net in trolley	T_{p1n}	lognormal	2.470	0.401	7
Place 2 nets in trolley	T_{p2n}	lognormal	3.424	0.160	13
Log 1 empty net (3 actions)	T_{t1n}	normal	10	1	2
Log 2 empty nets (4 actions)	T_{t2n}	normal	15	1	2

A simple accuracy criterion was used to indicate the quality of model calibration. It was defined as the ratio between the simulated mean and the measured result. With respect to the main model outputs Y_n, CT_n, CT_{sn} and C_o, the target accuracy was 0.95 to 1.05.

After calibration, a two stage validation was done based on data from the labour registration system only. In the first validation, harvester 34 was followed for 7 consecutive workdays in the time period July 14th to July 22nd, where he worked a greenhouse section alone. In a second validation, the model was tested for its performance during a longer time period with more active harvesters to determine the predictive value of the model. It involved a 96 days simulation for greenhouse section 2 in the time period, June 12th till September 18th, 2011. 27 different harvesters operated in 133 harvest cycles, 6 harvesters worked 5 or more days in section 2 and the other harvesters assisted occasionally in section 2, but were normally active in other greenhouse sections. The model parameters determined in the model calibration (Table 3.2) were used and not adjusted for individual harvester performance. Both validations were considered independent of the calibration based on the parameters obtained from the video recordings, since June 15th was not included, and in the second validation, harvester 34 participated in only 2% of the harvest cycles in section 2, harvesting 1% of the total number of roses. In both model validations, 4 run repetitions were used to smooth stochastic effects.

Model performance was evaluated for the key outputs labour time T_T, harvest rate C_o, number of roses harvested Y_n, travelled distance D_T, number of rose nets delivered N_{rnd}, and number of stems per delivered i^{th} rose net $n_{rnd}(i)$. For each output the mean squared deviation *MSD* between simulated and measured data was analysed according to Kobayashi and Salam (2000). The main quality indicator is relative root mean squared error $\mathrm{RRMSE} = \sqrt{\mathrm{MSD}}/\bar{y}$, where $\bar{y}$ is the measured mean. To allow assessment of RRMSE, MSD is decomposed into: 1) squared bias *SB*, i.e. the bias between simulation and measurement, which indicates if the model reproduces the measured mean correctly, 2) squared difference between simulated and measured standard deviations *SDSD*, which indicates if the model simulates the magnitude of fluctuation among the measurements correctly, and 3) the lack of correlation weighted by the standard deviations *LCS*, which indicates if the model reproduces the measured dynamic pattern of the signal correctly: MSD=SB+SDSD+LCS. Additionally, the correlation coefficient *r* between measured and simulated data was determined. For assessment of crop production systems, it was assumed that an RRMSE of 10% in labour time demand or less would be sufficient. Higher RRMSE is acceptable when the relative contribution of SB and SDSD in MSD is less than 10%, meaning that mean and standard deviation are predicted correctly, but pattern deviation occurs.

3.4.3 Simulated scenarios for growing system assessment

Model flexibility and added value was tested by simulating different harvest scenarios to show effects of worker skill, different equipment used, and different harvest management. Practically relevant and model challenging questions were addressed in these simulation scenarios: (Q1) What are the costs of new harvesters compared to average skilled workers?, (Q2) What labour cost reduction does a highly skilled worker realise for the company compared to average skilled workers?, (Q3) Are the costs for working with an electric trolley substantially less than the costs for use of hand pushed trolleys?, (Q4) What marginal financial yield is needed to make a second harvest cycle feasible?

A reference scenario S0 and four scenarios, S1-S4, were defined to answer the questions. The reference S0 represents the average skilled harvester 34, same as in the model calibration, using an electric trolley. The general settings for each scenario are listed in Table 3.3. Effects of the skill level of harvesters (Q1 and Q2) was simulated in scenarios S1 and S2. In S1, the new harvester is characterised by a doubled expected time requirement $E(T_i)$ and a less consequent working rhythm expressed as a 25% higher variance $V(T_i)$ for all basic stochastic actions *i*, a 25% lower trolley speed, and a later detection of a ripe rose at no more than 10 cm away from a ripe stem. In S2, the highly skilled harvester is characterised by a 20% better performance in the expected time demand $E(T_i)$ and a 10% lower variance $V(T_i)$ for all basic actions *i*, a 10% higher trolley speed, and an earlier detection of a ripe rose at 60 cm distance from a ripe stem. Scenario S3 was defined to answer Q3 on equipment. In S3, a hand pushed trolley with single buffer is used instead of an electric trolley with two buffers. The buffer capacity is 50% of that of an electric trolley. Each push impulse to the hand pushed trolley moves it 2 ripe rose positions along the rose bed. The roses cut on the way back to the trolley, are temporarily stored in hand. The push impulse is an additional basic action (number 9 in Fig. 3.2). Overlap between the actions 'buffer rose' and 'move along path' does not occur. The parameters T_{cr}, T_{stb}, T_{p1n}, T_{t1n}, and T_{bb} are assumed equal to those used for the electric trolley. In scenarios S0-S3, the second harvest cycle is assumed to have 24% of the daily yield, which is the measured greenhouse average for days with a second cycle. Q4 addresses harvest management. In scenario S4, the yield of the day is harvested in one harvest cycle using an electric trolley.

Table 3.3 - Model parameter settings for the scenarios S0-S4. v0 is operator velocity, Do is overlap distance 'move' and 'cut rose', *E(T_i)* and *V(T_i)* refer to expected value and variance of the basic stochastic actions given in Table 3.2, n_{hc} indicates number of harvest cycles, *Eq* indicates the trolley type used. (*) Reference to the full parameter set in Table 3.2, and (**) reference to a limited parameter set in Table 3.2 (*Tcr*, *Tstb*, *Tp1n*, *Tt1n*, and *Tbb*) and an assumed pdf(*Tpb*) equal to pdf(*Tstb*).

Scenario	Description	v_o (m s^{-1})	D_o (m)	$E(T_i)$ (s)	$V(T_i)$ (s)	n_{hc} (-)	*Eq* (-)
S0	Reference	0.39	0.5	*	*	2	electric
S1	New harvester	-25%	0.1	+100%	+25%	2	electric
S2	Skilled harvester	+10%	0.6	-20%	-10%	2	electric
S3	Hand pushed trolley	0.39	0.5	**	**	2	hand-pushed
S4	1 harvest cycle	0.39	0.5	*	*	1	electric

Scenario effects were assessed for 5 crop yield levels within practical range, 0.5, 1.0, 1.6, 2.0, and 3.0 stems m^{-2} per day. For each yield level and each scenario, one day was simulated and the outcome of a simulation is the mean of four model run repetitions. Labour time T_T and cost effects per 1000 roses were determined by comparison with the reference scenario *S0*. For all workers a fixed labour cost level of 16 € h^{-1} was assumed. The purchase value of a height adjustable electric trolley and a hand pushed trolley was € 6000,- and € 570,- respectively. Taking in account interest (6%), depreciation (10%) and maintenance (3 and 1% respectively), the investment cost per 1000 harvested roses was estimated at € 2.35 and € 0.20 respectively, when two units were available per greenhouse section.

3.5 Results and discussion

Simulated results in the Sections 3.5.2 and 3.5.3 were not given a variation interval around the points since the main interest in this paper was to demonstrate the ability to evaluate different scenarios based on the mean output of the model and not to provide specific analysis.

3.5.1 Model calibration for one harvester in one harvest cycle

Model calibration was done for one full harvest cycle in greenhouse section 2 based on video recorded data of harvester 34. Results are presented in Table 3.4.

Table 3.4 - Model calibration results for harvest cycle June 15th, 2011 (7:45-11:00 h) in section 2 by harvester 34. Comparison of main performance parameters of the harvest process. Model accuracy is indicated as the ratio between simulated mean for 10 runs and measured result. The 95% confidence level for the simulated mean is indicated in brackets ($\pm$ci).

Performance indicator	Symbol	Measured	Simulated mean($\pm$ci)	Accuracy
Yield in harvest cycle 1 (stems)	Y_n	1,593	1,581 ($\pm$105)	0.99
Cycle time section (s)	CT_n	10,693	10,442 ($\pm$383)	0.98
Cycle time subnode (rose-bed)	CT_{sn}			
Mean (s)		391	405 ($\pm$16)	1.04
Std. (s)		95	98 ($\pm$19)	1.03
Harvest rate (stems h^{-1})	C_o	557	545 ($\pm$9)	0.98
Average speed in path (m s^{-1})	v_o	0.18	0.18 ($\pm 6.2 \cdot 10^{-3}$)	0.97
Rose nets delivered (-)	N_{rnd}	13	12 ($\pm$0.6)	0.92
Mean number of roses per net (-)	$\overline{n}_{rnd}$	122.5	131.8 ($\pm$5.1)	0.93
Time per bundle in main aisle (s)		69	59 ($\pm$1.6)	0.85
Cumulative distance operator (m)	D_T	1,728	1,981 ($\pm$11)	1.15

All time related performance indicators in Table 3.4, with exception of the time per bundle in the main aisle, have less than 5% error compared to measured data, which is well above the target for validation. Besides for these indicators measured results are within the confidence interval of simulated results. Probable causes of the lower accuracy in time per bundle are the low number of observations on rose net delivery actions and some deviation between individual harvester behaviour and the decision tree for unloading rose nets. The measured cumulative travelled distance by the operator D_T is restricted to the travel distance in cultivation paths, twice the total path length (1728 m), since actions outside the trolley were not video recorded. Simulated result (1981 m) is the cumulative distance including work in main aisle and moving to the section. Thus, the model accuracy on D_T is better than indicated in Table 3.4.

The section cycle time CT_n was decomposed into pure cut time T_{Tc} , pure transport time T_{Tt}, overlap time T_{To} as indicated in Section 3.3.4.4, rose net handling time T_{Tr}, wait time T_{Tw}, and rose review time without cutting. The relative contribution of these terms was respectively 51 (45), 21 (22), 21 (23), 7 (8), 0 (0), and 0 (2)%. Un-bracketed numbers indicate simulated, bracketed numbers indicate measured contributions. Rose reviewing without cutting was not implemented in the model. The decomposition of CT_n shows that also at a lower decomposition level the model represents measured data adequately.

3.5.2 Model validation

A model validation of one harvester for one week was carried out, followed by a 3 months validation of one section of the greenhouse with 27 different harvesters.

3.5.2.1 One harvester one week

Seven workdays on which harvester 34 harvested a complete greenhouse section were used in this validation. The results presented in Fig. 3.3 show that the harvest rate is well described by the model. Measured mean harvest rate C_o is 564 and simulated mean is 570 stems h^{-1}, RRMSE is 4.5%, and correlation coefficient r=0.94. Simulated and measured mean labour time was 3 h 59 min and 4 h 2 min respectively, RRMSE is 4.4%, and r=0.99.

Roses were assigned to beds by a random function. Therefore the total number of roses harvested was compared. The measured mean was 2332 and simulated mean 2330 stems per day, and RRMSE= 3.3%. Labour time, harvest rate and the total of roses harvested match well, with errors (RRMSE) less than 5%. This is within the stated limit for RRMSE of 10%. Over 90% of the errors was explained from differences in the pattern of measurements and simulations.

On July 19th and 21st a second harvest cycle was realised. The model accumulates the travelled distance by trolley and by foot in one accumulated number per harvest cycle in D_T. Simulated mean travelled distance in harvest cycle 1 was 2046 m, and 1823 m in harvest cycle 2. The real travelled distance was not registered, but simulated D_T is feasible when compared to the 1728 m travel distance within cultivation paths in a greenhouse section, since walking to the section, handling of rose bundles in the main aisle, and moving between paths is included in the simulation. Finally, the number and fill status of rose bundles delivered were compared. The number of bundles in harvest cycle 1 in measured and simulated situation were 16.6 (SD=5.4) and 16.5 (SD=5.4) respectively with RRMSE=12.9%. RRMSE is fully explained from differences in the pattern of measured and simulated data. The maximum difference in daily delivered rose bundles was 4. The overall average fill status of the bundles delivered during the 7 days was 138 stems (SD=37.5) and 135 stems (SD=42.8) for the real and simulated system respectively.

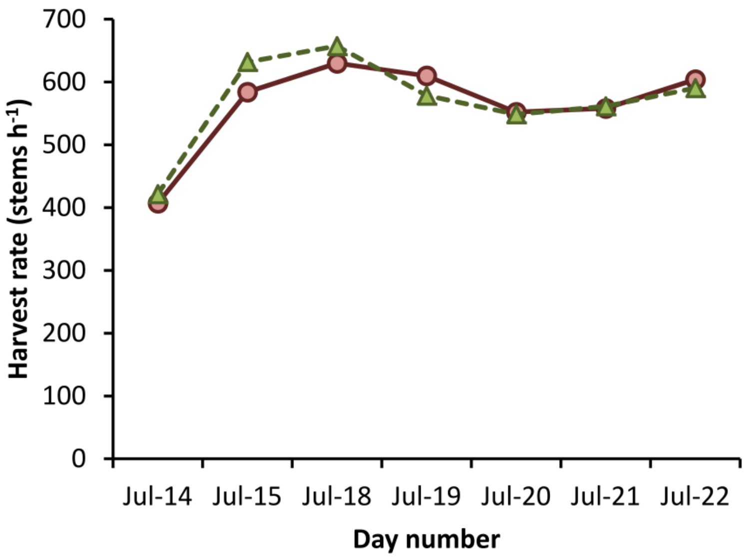

Fig. 3.3 - Measured (—o—) and simulated (--▲--) harvest rate C_o of harvester 34 during 7 consecutive workdays, mid July 2011 (r=0.94).

3.5.2.2 One section for 3 months

The model was validated over a longer time period with more active harvesters and a larger range in yield in order to determine the predictive value of the model with given fixed parameters. The accuracy in the daily rose yield resulting from random assignment of ripe stems to rose beds was comparable with the previous validation (RRMSE=3.5%). Daily measured and simulated labour time T_T for harvest activities in greenhouse section 2 is given in Fig. 3.4. The accuracy of the model was less than in the one week validation with RRMSE= 15.2%. However the correlation coefficient between simulated and measured data remains high, r=0.94. Based on analysis of the mean squared deviation, it became clear that the deviation is caused by the model not simulating the exact pattern of the fluctuation across the measurements (LCS MSD ratio > 0.99). The model, however, predicts mean and standard deviation in labour time very well. A probable explanation is difference in harvest rate of individual harvesters (skill). From Fig. 3.5 it is clear that at the end of June and the beginning of July a highly skilled harvester is active in section 2 causing a higher harvest rate than simulated. Measured mean harvest rate between June 23rd and July 9th was 629 stems h^{-1} and simulated mean harvest rate was 553 stems h^{-1}. Data revealed that harvester 5 with mean measured harvest rate C_o 652 stems h^{-1} was responsible for 14 out of 19 harvest cycles in this period. At the beginning of September new personnel was trained in section 2 causing the effective harvest rate to drop to 300 stems h^{-1}. The increased RRMSE in Fig. 3.4 can therefore be explained from the absence of individual harvester parameters in the model. Probable other causes for these pattern differences could be trolley speed deviation, inaccurate time logging in practise or errors in the labour registration system.

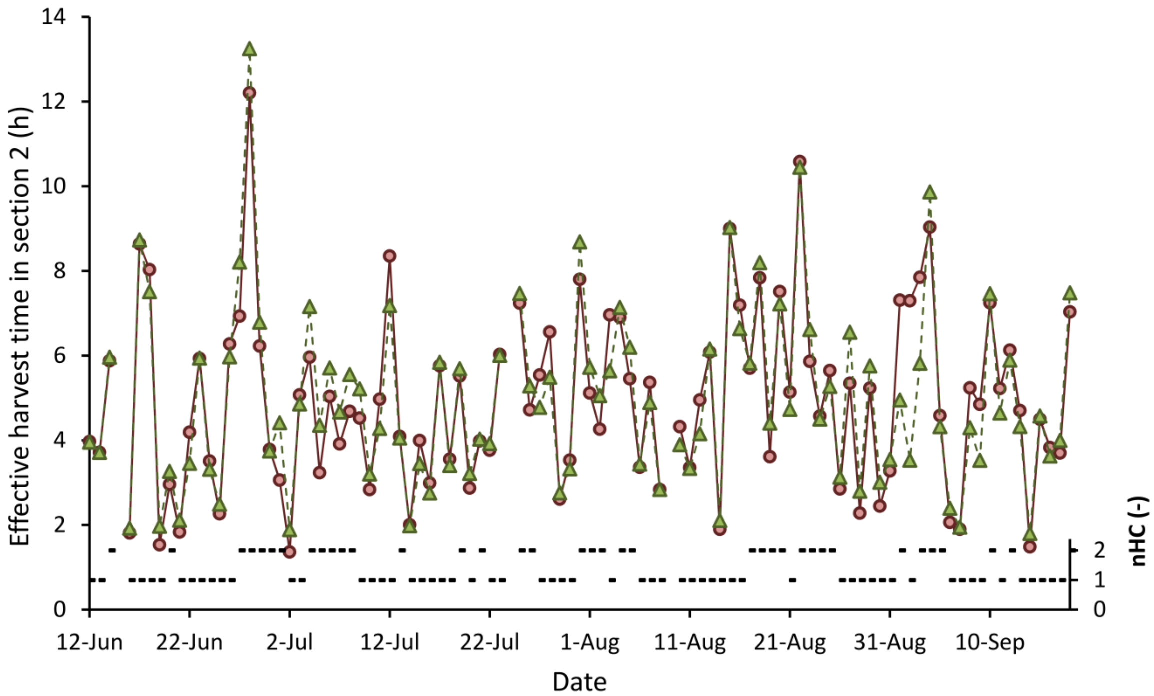

Fig. 3.4 - Validation results, measured (—o—) and simulated (- -▲- -) effective daily harvest labour time T_T in section 2 (1800m^2) during 96 days in summer 2011 (period June 12th till September 18th). The number of harvest cycles per day n_{hc} is given in the second axis (-). RRMSE= 15.2%, r= 0.94.

The dynamics of measured and simulated harvest rate C_o, given in Fig. 3.5, show similar pattern with Fig. 3.4, but also clear differences, RRMSE= 13.6% and r= 0.63. The LCS MSD ratio is 0.97, meaning that the model predicts mean and standard deviation in harvest rate correctly, but daily differences between measured and simulated result exist. This is supported by the decreased correlation coefficient.

In comparison, the harvest rate on the model calibration day, June 15, was 546 stems h^{-1}. Harvest rate depends on the parameters specified in Table 3.2, rose yield and trolley speed. A high correlation coefficient between the deviation in total labour time for harvest and the deviation in harvest rate (r=0.92) supports the conclusion that RRMSE is mainly caused by absence of individual harvester parameters in the model.

Simulated and measured data were also compared with focus on a 2nd harvest cycle, on activating a second harvester, and on the handling of rose bundles. A second harvest cycle was realised on 37 days. Both in simulated and measured data 11% of the total of roses in section 2 was harvested during the second harvest cycle and respectively 15% and 14% of total harvest labour time in the greenhouse was used. In simulation and measured data a second harvester was added to greenhouse section 2 during 17 (4) and 24 (10) days respectively. The bracketed numbers indicate how often this harvester acted in section 2 for less than 1 h.

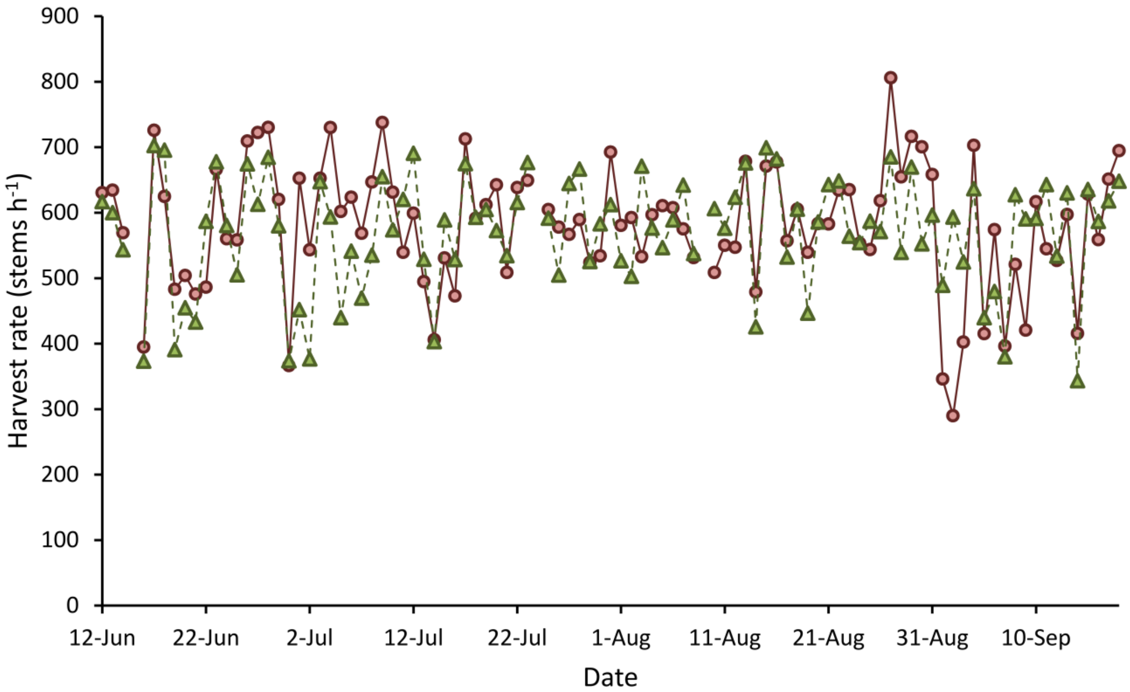

Fig. 3.5 - Measured (—o—) and simulated (- -△- -) daily averaged harvest rates C_o in section 2 (1800m^2) during 96 days in summer 2011 (period June 12th till September 18th). RRMSE= 13.6%, r= 0.63.

In simulated and measured data, a total of respectively 1771 and 1614 rose bundles were delivered with a mean fill rate of 159 and 174 roses, respectively. The time series of daily number of rose bundles delivered has RRMSE=33.9%, and *r*=0.66. MSD-analysis further indicates that model bias explains 7%, standard deviation difference 3% and pattern differences 90% of MSD. So, also here pattern differences are the main cause of deviation. This higher RRMSE for rose bundles contributes to RRMSE in total labour time with a strongly reduced effect since bundle handling time is less than 10% of total labour time.

3.5.3 Simulated scenarios

Model flexibility and added value was tested by means of scenario simulations comparing scenarios S1-S4 with the baseline scenario S0, to show effects of worker skill, of different equipment used and of the harvest management decision to work with or without a 2nd harvest cycle. The results for simulated scenarios on different skill level of harvesters S1 and S2 is given in Fig. 3.6.

From Fig. 3.6a, it is clear that harvest labour time T_T in *S0* and *S2* is almost proportional with yield. The slope of the line is affected by worker skill. For a new harvester as simulation in *S1* at 3 stems m^{-2} this proportionality is lost. At this high yield level insufficient time was available to start the second harvest cycle before 17:00 h, thus forcing the simulation to omit it. The harvested yield was 2.2 stems m^{-2}. The simulated harvest rate C_o of the average

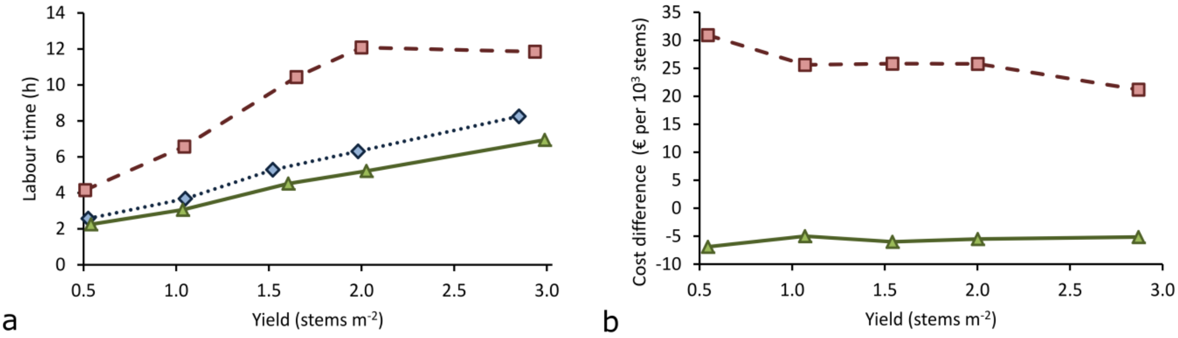

Fig. 3.6 - Harvest labour time T_T (h) (a), and the cost difference with the reference scenario € per 1000 stems (b). Scenario S1 new harvester ( ), scenario S2 highly skilled harvester ( ) compared to the reference scenario S0 average skilled harvester ( ).

harvester ranged from 346 stems h^{-1} at *Y(d,n)*=0.5 stems m^{-2} to 615 stems h^{-1} at *Y(d,n)*=3.0 stems m^{-2} and that of a new harvester from 207 stems h^{-1} at *Y(d,n)*=0.5 stems m^{-2} to 339 stems h^{-1} at *Y(d,n)*=3.0 stems m^{-2}, which is close to what a grower expects. In answer to Q1), compared to an average harvester *S0*, the cost increase (Fig. 3.6b) resulting from extra labour time input of a new harvester ranges from 21.2 € per 1000 roses at high yield to 30.9 € per 1000 roses at low yield when wages are not differentiated. The simulated harvest rate C_o of the highly skilled harvester *S2* ranged from 407 at *Y(d,n)*=0.5 stems m^{-2} to 767 stems h^{-1} at *Y(d,n)*=3.0 stems m^{-2}. In answer to Q2), the highly skilled harvester decreases labour costs with 5.2 - 6.9 € per 1000 roses compared to the average harvester *S0*. It is clear that the indicated cost effects are substantial, especially when compared to the average 121 min harvest labour time spent per 1000 roses as determined from the data, which is equivalent to € 32.2 per 1000 stems. A grower should maintain a minimum standard on harvest performance since worker skill has a big impact on labour cost. Positive feedback to employees on their performance can help realise a constant team of highly skilled and motivated harvesters.

In Fig. 3.7, the result for scenario *S3* on different equipment is given.

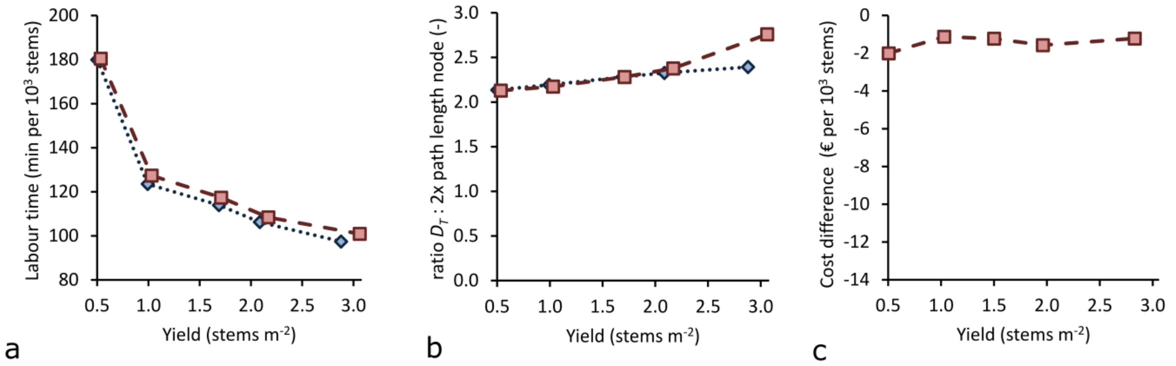

Fig. 3.7 - Comparison of a hand pushed trolley (S3) with an electric trolley (S0), 2 harvest cycles per day. Harvest labour time T_T per 1000 stems (min) (a), ratio cumulative distance travelled by operator D_T and twice the section path length (-) (b), and cost difference with the electric trolley S0 in € per 1000 stems (c). Hand pushed trolley ( ) and an electric trolley ( ).

With respect to question Q3, with given model assumptions, the labour time demand for the hand pushed trolley is on average 3% higher, but application of this trolley results in a cost decrease between 0 and 2 € per 1000 stems as a result of lower investment costs (Fig. 3.7c). The hand pushed trolley takes slightly more time since it cannot take advantage of time overlap between the actions 'rose to buffer' and 'move along path', nor of paired unloading of rose nets, and time is required for push impulses. However, it has a time advantage in buffering cut roses in the hand. The overlap time advantage for the electric trolley first increases with yield to decrease again at yield levels around 1.5 stems m^{-2}, however at high yields (>2 stems m^{-2}), the lower buffer capacity in the hand push trolley becomes an issue because the trolley has to leave a path for unloading more often, thus increasing labour time demand. This clearly shows in Fig. 3.7b, where travel distance increases due to intermediate unloading. Intermediate unloading hardly occurs with electric trolleys. The effects discussed show in the cost difference curve in Fig. 3.7c.

The result for simulated scenario *S4*, different harvest management, is given in Fig. 3.8.

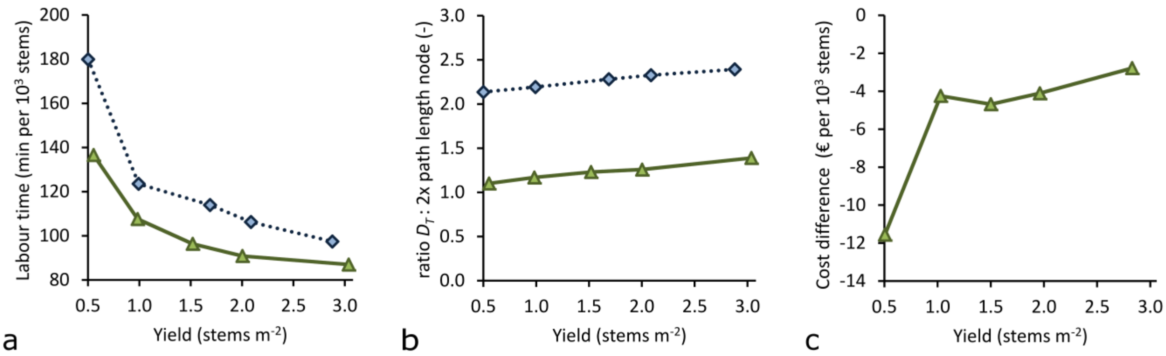

Fig. 3.8 - Comparison of 1 harvest cycle (S4) with 2 harvest cycles (S0), both with use of an electric trolley. Harvest labour time T_T per 1000 stems (min) (a), ratio cumulative distance travelled by operator D_T and twice the section path length (-) (b), and cost difference S4-S0 in € per 1000 stems (c). Electric trolley, 1 harvest cycle (), Electric trolley, 2 harvest cycles ( ).

With respect to Q4, skipping the second harvest cycle improves all labour performance indicators, having a lower labour time, better harvest rate, and less travel distance. Lower labour costs result. However, the cost reduction decreases with yield. As a result of the 2nd harvest cycle, at low yield the labour cost increase with € 11.5 per 1000 roses, and at the highest yield with € 2.8 per 1000 roses. During the 2nd cycle at daily yield < 1 stems m^{-2}, v_o is equal to trolley cruise speed and at higher yield v_o is 0.39 m s^{-1}, and this causes the change in the course of the cost line (Fig. 3.8c) between 1 and 1.5 stems m^{-2}. With increasing yield the advantage of parallel actions, overlap time T_{To}, is higher for 2 harvest cycles, and thus compensates for a small part (8 min) of the extra move time T_{Tt} required for the 2nd harvest cycle. The extra cost for a second harvest cycle is only profitable if it is compensated by extra financial yield resulting from better product quality.

In conclusion it can be stated that economic effects of trolley choice are small (0-2 € per 1000 stems). Working with electric trolleys is slightly more time effective, but costs are higher as a result of higher investment costs. Costs of a second harvest cycle are substantial (€ 2.8 - € 11.5 per 1000 stems), especially at low daily yield. A second harvest cycle is only feasibility if yield quality effects compensate for the extra costs. Overall, the model is able to run scenarios to help provide answers for (grower) questions and to help reflect on ideas on work method improvement and on innovation by design.

3.6 Conclusions

The GWorkS model (Van 't Ooster et al., 2012) was easily adapted to simulate a static growing system for cut-rose without altering the generic model structure, provided it was extended with static growing system specific properties and process elements. The model validation showed that the adapted model performed well in terms of different operations performance indicators. With use of one fixed parameter set on harvester performance the mean and standard deviation in a data set on labour time is explained accurately. MSD analysis on time series of measured and simulated harvest labour time and harvest rate showed that more than 90% of RRMSE could be explained from times series pattern deviation mainly resulting from individual differences between workers. The work scenario study showed that worker skill affected labour performance considerably and that it is economically feasible to pay attention to labour management and worker team skill. Working with electric trolleys is slightly more time effective than working with hand pushed trolleys, but costs are higher as a result of higher investment costs. From an economic point of view with given model assumptions, it is not feasible to use electric trolleys. Cost of a second harvest cycle are substantial, especially at low daily yield. A second harvest cycle is only feasible if yield quality effects would compensate for the extra costs (0.2-1.1 cent per rose). GWorkS scenario studies are easily performed, so it is a good tool for decision support as it gives clear answers to (grower) questions using the full complexity of the harvest process. Overall conclusion is that the adaptability and transferability of the generic model concept has been proven and specifically validated through the case of a static growing system for cut-roses. The model was successfully used in scenario studies on harvest in roses and it is ready for use in design studies on harvest processes in greenhouses.

3.7 Acknowledgements

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3.8 References

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Chapter 4

Sensitivity analysis of a stochastic discrete event simulation model of harvest operations in a static rose cultivation system

A. van ’t Ooster, J. Bontsema, E.J. van Henten, S. Hemming

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4 Sensitivity analysis of a stochastic discrete-event model of harvest operations in a static rose cultivation system

4.1 Abstract

Greenhouse crop system design for maximum efficiency and quality of labour is an optimisation problem that benefits from model-based design evaluation. This study focussed on the harvest process of roses in a static system as a step in this direction. The objective was to identify parameters with strong influence on labour performance as well as the effect of uncertainty in input parameters on key performance indicators. Differential sensitivity was analysed and results were tested for model linearity and superposability and verified using the robust Monte Carlo analysis method since in literature, performance and applicability of differential sensitivity analysis is questioned for models with internal stochastic behaviour. Greenhouse section length and width, single rose cut time, and yield influence labour performance most, but greenhouse section dimensions and yield also affect the number of harvested stems directly. Throughput, i.e. harvested stems per second, being the preferred metric for labour performance, is most affected by single rose cut time, yield, number of harvest cycles per day, greenhouse length and operator transport velocity. The model is insensitive for σ of lognormal distributed stochastic variables describing the duration of low frequent operations in the harvest process, like loading and unloading rose nets. In uncertainty analysis the coefficient of variation for the most important outputs labour time and throughput is around 5%. Total sensitivity as determined using differential sensitivity analysis and Monte Carlo analysis essentially agreed. The combination of both methods gives full insight in both individual and total sensitivity of key performance indicators.

Nomenclature

symbol	*description and unit*
C_o	Individual harvest rate of an operator (stems h^{-1})
CT_n	Cycle time of node *n* (s)
CT_{sn}	Cycle time of subnode *sn* (s)
CV	Coefficient of variation
d_{hc}	Decision parameter, allowed number of harvest cycles ($d_{hc} \in [1,2]$)
D_o	Overlap distance between a move action and a basic rose cut action (m)
D_s	Stochastic variable distance between ripe stems (m)
$D_T(n,k)$	Cumulative travel distance operator since t_0 within task *k* in node *n* (m)
Δy_i, $\Delta y_{i,j}$	Individual absolute sensitivity of output y_i for perturbation in parameter p_j
$\Delta y_{i,tot}$	Total absolute sensitivity of model output y_i for perturbation of a parameter vector *P*
$E(\nu)$	Expectation of stochastic variable ν
hc	Daily harvest cycle index $hc \in [1, 2]$(-)
L_{Gh}	Greenhouse length in ridge direction (m)
$LT(n,k)$	Lead time on job element *k* in node *n*, a management constant indicating target process time
μ	Mean of the variables natural logarithm for pdf-type $LN(\mu,\sigma^2)$ or the variable itself for pdf-type $N(\mu,\sigma^2)$
N	Number of Monte Carlo simulations
n_p	Number of parameters in analysis (-)
$N_{rnd}(n)$	Number of rose nets delivered in node *n* (-)
n_{sp}	Number of spans per node $n_{sp} \in [1, 2, 3, 4]$ (-)
n_y	Number of outputs in *y* (-)
P	Model parameter vector $P=(P_g\ P_c\ P_o\ P_m)$
P'	Parameter vector used in DSA test, $P' \in P$
P"	Parameter vector used in uncertainty analysis, $P'' \in P$
p_j	Individual model (input) parameter subjected to sensitivity analysis
$p_\nu(\nu)$	Probability density function of the stochastic variable ν
σ	Standard deviation of the variables natural logarithm for $LN(\mu,\sigma^2)$ or the variable itself for $N(\mu,\sigma^2)$
SD	Standard deviation (data set)

symbol	*description and unit*
$S_{i,j}$	Normalised sensitivity coefficient of output y_i for (input) parameter p_j (-)
t_0, t_f	Start and end time of simulation (s)
T_{bb}	Stochastic variable service time to bind a rose net to a bundle (s)
T_{cr}	Stochastic variable service time to cut a single rose (s)
$TH(n,k)$	Throughput of product, average output of task *k* in node *n* per unit time (s^{-1}), *k*=1 is harvest, *TH(n,1)* is output of harvested stems s^{-1} of CT_n
T_{p1n}, T_{p2n}	Stochastic variable service time to place one, two empty rose nets in the trolley (s)
T_{stb}	Stochastic variable service time to place a single rose in the trolley buffer (s)
$T_T(n,k)$	Total labour time on task *k* in node *n* (s)
T_{t1n}, T_{t2n}	Stochastic variable service time to log one, two empty rose nets in the labour registration system (s)
$T_{Tc}(n,k)$	Total cut time within harvest task in node *n* (s)
$T_{To}(n,k)$	Total overlap time between actions within task *k* in node *n* (s)
$T_{Tt}(n,k)$	Total transport time within task *k* in node *n* (s)
$T_{Tw}(n,k)$	Total wait time within task *k* in node *n* (s)
$u_o(o)$	Utilisation of operator *o*
v_o	Operator velocity at task execution (m s^{-1})
ξ	Gaussian random variable with $\mu = 0$ and $\sigma = 1$
y	Vector holding key performance indicators of the model
y_i	Individual performance indicator, $y_i \in y$
Y_n	Measured yield of the day in node *n* (stems m^{-2})
$Y_{n\,cf}$	Gain factor representing a correction in measured yield Y_n (-)

4.2 Introduction

Labour is a dominant cost factor in Dutch cut-rose production. Growers feel an economic need to decrease labour cost and control labour demand better. Crop production system design and labour management are the key processes for improving labour efficiency. These processes are commonly driven by system evolution and experience. Quantitative models for evaluation of new crop production system designs and new labour management strategies are not available. For this reason the Greenhouse Work Simulation model (GWorkS) was developed. In Van ’t Ooster, Bontsema, van Henten, and Hemming (2012, 2014), this model was presented and validated for harvest in two crop production systems for cut rose, a mobile and a static rose production system. GWorkS is a stochastic discrete event model on crop operations in greenhouses. Its purpose is to support designers and growers in improving crop cultivation systems with respect to labour efficiency and quality of labour.

For model based design and evaluation of systems, it is required to evaluate 1) risks of model or system failure resulting from uncertainty, and 2) sensitivity of key performance indicators for individual parameters. Sensitivity analysis is the suitable technique for both (Macdonald & Strachan, 2001). The aim of this study was to identify 1) input parameters that must be chosen with care so as not to compromise the accuracy of the model prediction as well as parameters for which accurate specification is less necessary, 2) features of the growing system to which labour demand is very sensitive and which could guide the designer and producer of a growing system to an improved system, and 3) impact of model limitations and sources of uncertainty on the models ability to discriminate between alternative work scenarios.

Delivering the aims of this study requires determination of individual sensitivity and uncertainty ranges of model output. Individual sensitivity describes effects of individual parameters on model output. Differential sensitivity analysis (DSA) is widely used to produce individual sensitivity (Lomas & Eppel, 1992). In this study, DSA is a one-at-a-time method varying just one parameter for each simulation while all other parameters remain fixed at their nominal value (Hamby, 1995). The change in a model output is a direct measure of the effect of the change in the single input parameter. However, in a stochastic model, this direct measure may be disturbed by random internal processes. For linear and superposable systems in the parameter space, DSA also produces total sensitivity by taking the length of the vector containing the individual sensitivities. This total sensitivity describes the output effect of perturbation of all parameters. If input perturbation equals the measured input uncertainty, then total sensitivity represents output uncertainty. When assumptions are met and when disturbance by internal random processes is excluded, DSA is an ideal and fast method for determining both parametric sensitivity and uncertainty. Gunawan, Cao, Petzold, and Doyle III (2005) and Kim, Debusschere, and Najm (2007) indicate that DSA does not directly apply to discrete stochastic dynamical systems and therefore its application in this study is not obvious since the GWorkS-rose model is a model of this type. It will however be shown with help of Monte Carlo analysis (MCA) that in this case application of DSA is appropriate. MCA is a more rigorous method in determining uncertainty, since no specific assumptions on the model are required. MCA involves simultaneous variation of all inputs. The variation of the inputs is random within a defined probability density function. The method fully accounts for interactions between inputs, for internal random processes and it is not affected by the number of parameters (Macdonald & Strachan, 2001). MCA generates total sensitivity only (Lomas & Eppel, 1992). If both methods, DSA and MCA, agree with respect to total sensitivity, then DSA is a credible and fast method that can be used for determining individual sensitivity.

4.3 Modelled system

4.3.1 Static cut-rose production system

The focus of this study is the harvest process in a static rose cultivation system in a greenhouse in The Netherlands. In this production system, roses are grown on irrigated substrate-filled gutters at a plant density of around 6 plants m^{-2}. The static gutters are positioned at 0.5 to 1 m above floor level and stretch from a centred main aisle to a side wall. Four gutters make a rose bed which has 2 adjacent paths alongside. In the paths, harvest is done one-sided by a harvester using an electric trolley for transport and buffering of cut stems. Normally three greenhouse spans are grouped into a greenhouse section to form a work unit of about 1800 m^2 for one harvester. Only in case of high yield will a second harvester assist. On days with fast ripening of roses, the grower may plan a 2nd harvest cycle on the same day. More details are given in Van ’t Ooster et al. (2014).

4.3.2 GWorkS-rose model

The main structure of the greenhouse work simulation model for roses, GWorkS-rose, is given in Fig. 4.1. The queueing network represents a job routing scheme for simulation of daily labour processes in a rose producing greenhouse. The main process is harvesting flowers. Other process models, like pinching of flower bearing axillary bud breaks, and bending of flowerless shoots will be included at a later stage of the research and are left outside the current study. The current model works with measured yield. Therefore, number of harvested stems does not depend on plant density. The GWorkS-rose model is implemented in Matlab®, Simulink® and SimEvents®.

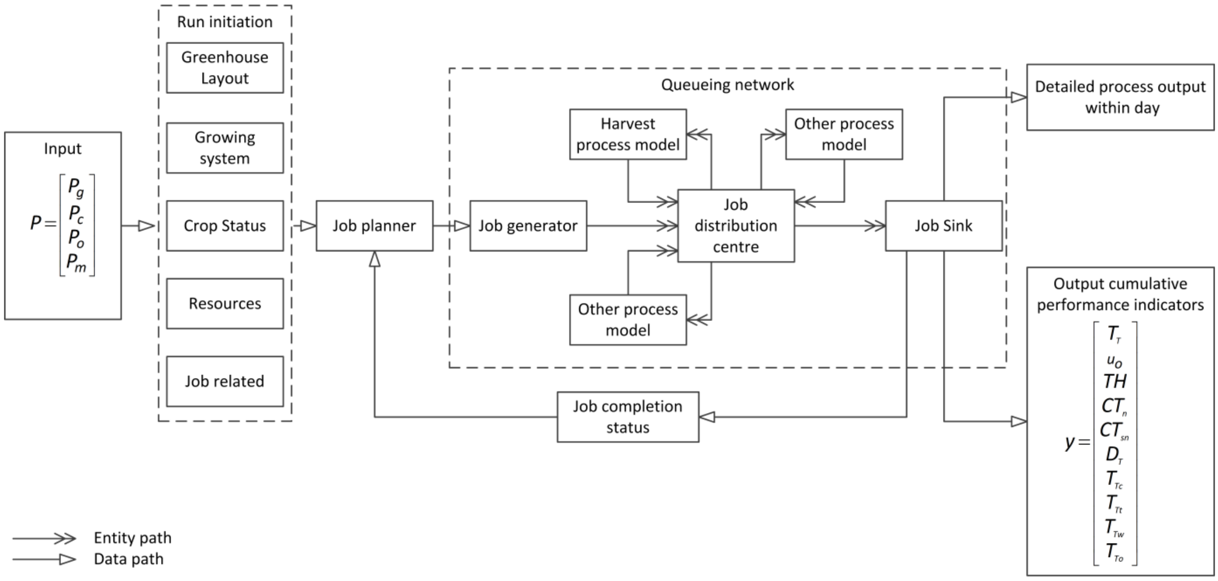

Fig. 4.1 - Main structure of the GWorkS-rose model. Symbols of individual parameters are given in the nomenclature.

The evaluated model input is defined as parameter vector P which consists of 4 sub-vectors: 1) greenhouse-related parameters P_g defining the physical greenhouse layout, 2) crop-related parameters P_c defining crop system layout and crop status, i.e. the demand for crop handling processes, 3) operator and facility-related parameters P_o, and 4) greenhouse management parameters P_m. On a daily basis, it is assumed that P is time-invariant. Greenhouse management is expressed in terms of a model-generated daily plan for process execution based on task frequency, model-recorded history of task execution, expected workload and target cycle times. The plan assigns tasks and resources to greenhouse sections. From the job generator onwards the model is a discrete event system. In the process models, the queueing network has probability density functions for service times and for spatial distribution of basic human actions in the crop handling processes. The spatial distribution of actions is mainly determined by the positions of ripe roses. These positions result from sampling probability density functions on number of ripe roses per subnode, i.e. one path side, and on positioning the roses along a subnode. The model has deterministic service times for transportation.

The performance vector y contains key performance indicators for greenhouse labour, represented by cumulative model output on a daily basis. Vector y consists of the elements y_i, total daily labour time T_T (y_1), utilisation u_o of two workers (y_2, y_3), product throughput TH (y_4), for two harvest cycles hc= (1, 2), cycle time per greenhouse section $CT_n(hc)$ (y_5, y_6) and cycle time per rose bed $CT_{sn}(hc)$ (y_7, y_8), operator transport distance D_T (y_9), cumulative cut time T_{Tc} (y_{10}), cumulative transport time T_{Tt} (y_{11}), cumulative wait time T_{Tw} (y_{12}), cumulative overlap time moving-cutting T_{To} (y_{13}), and number of rose nets delivered N_{rnd} (y_{14}). The accumulation interval is t_0(s) to t_f(s). Start t_0 and end time t_f are limited by a block function defining maximum work hours.

4.4 Sensitivity analysis

To satisfy the research aims, both individual and total sensitivity are required. The main structure of the sensitivity analysis for DSA and MCA is given in Fig. 4.2. The sensitivity analysis was carried out in Matlab®. DSA was applied to determine individual sensitivity at five nominal levels of crop yield Y_n representative for the underlying summer data set (June 12th to September 18th, 2011). The method is described in Section 4.4.1. MCA produces full probability density distribution of individual outputs y_i. MCA was not only used as the leading method to determine uncertainty in model output (Section 4.4.2) but also to verify whether total sensitivity as predicted by DSA is accurate and whether use of DSA in determining individual sensitivity was justified in this case (Section 4.4.3).

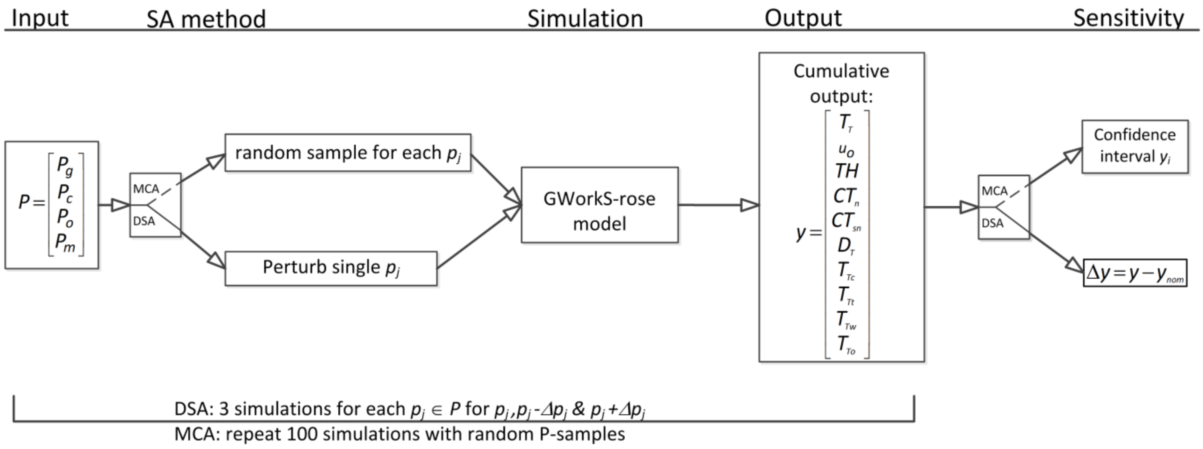

Fig. 4.2 - Sensitivity analysis scheme for differential sensitivity analysis (DSA) and Monte Carlo analysis (MCA) for use with the GWorkS-rose model. DSA uses 3 simulations per parameter p_j, MCA 100 simulations for parameter vector *P*.

Total sensitivity serves more purposes: 1) finding the combined influence of input parameters on the predicted output, 2) test on linearity and superposability assumptions in DSA (DSA-test), and 3) verification of the DSA results for this case, since total sensitivity is the key connection between DSA and MCA. The linearity assumption is true if model outputs react linear to $p_j \in P$ and the superposability assumption is true if effects of parameter perturbations are independent of each other. Then, DSA supplies an accurate approximation of total sensitivity, thus allowing true comparison of DSA with MCA result.

4.4.1 Individual sensitivity

DSA involves varying one element in parameter vector *P* each simulation to determine the resulting change in the model outputs, a single-variate differential sensitivity analysis. The single-variate sensitivity is defined using the normalised sensitivity coefficient (Lomas & Eppel, 1992):

$$S_{i,j} = \frac{\Delta y_{i,j}}{\Delta p_j}\frac{p_j}{y_i} \tag{1}$$

where the individual sensitivity $\Delta y_{i,j}$ is given by:

$$\Delta y_{i,j} = \Big(y_i\left(p_1, p_2, \ldots, p_{j-1}, p_j \pm \Delta p_j, p_{j+1}, \ldots, p_{n_p}\right) - y_i\left(p_1, p_2, \ldots, p_{j-1}, p_j, p_{j+1} \ldots, p_{n_p}\right)\Big),$$

which represents the elementary effect of parameter p_j in y_i (Morris, 1991), $\frac{p_j}{y_i}$ is the scaling factor which removes the effects of units (Vanthoor, van Henten, Stanghellini, and de Visser, 2011). A perturbation of 1% in p_j results in a perturbation of $S_{i,j}$ % in y_i. If $|S_{i,j}|>>1$, output y_i is very sensitive for parameter p_j. If $|S_{i,j}|<<1$, output y_i is insensitive for parameter p_j. For linearity assessment, if $S_{i,j}$ is equal for $+\Delta p_j$ and $-\Delta p_j$, then the system can be considered linear in its response to input p_j for given perturbation. For each parameter, three simulations were executed for p_j, $p_j+\Delta p_j$, and $p_j-\Delta p_j$ (Fig. 4.2). With integer parameters, a perturbation Δp_j of 1 was used and for real parameters a 1% perturbation was used to find the individual impact of parameter p_j. The parameter vector $P=(P_g, P_m, P_o, P_c)$ was subjected to DSA with estimated nominal values resulting from experimental data reported in Van 't Ooster et al. (2014). *P* is given in Table 4.1.

Internal random processes in the model generate variations in model output even for a constant *P*. In DSA simulations, fixed random generator seeds were used for internal probability density functions to assure repeatable results in consecutive simulations for determining $S_{i,j}$. This procedure separates the effects of internal random processes from parameter perturbation. Thus interference of these effects is avoided and individual sensitivity could be determined based on three model runs per parameter p_j. However, doing so reduces stochastic behaviour of the model to a 'frozen' series of random numbers and sensitivity estimates might be affected. This was an additional reason to verify DSA total sensitivity results using MCA since MCA takes full stochastic behaviour into account.

For interpretation of results, the model was considered sensitive to parameter p_j if in a series of nominal values for p_j, $\max|S_{1,j}|\geq 0.1$, where i=1 represents labour time T_T. Low sensitive if $0.01\leq\max|S_{1,j}|<0.1$ and insensitive if $\max|S_{1,j}|<0.01$. These numbers were chosen this low since a 1% change in labour time represents already an order of magnitude of 0.5 € m^{-2} y^{-1}. Also, throughput TH (stems s^{-1}) defined as average output of the production process per unit time (Hopp & Spearman, 2008) is an important criterion in identifying relevant parameters for system improvement. Sensitivity coefficient, $S_{4,j}$, where i=4 represents throughput, was used to indicate yield-corrected labour sensitivity. Impacts of p_j, measured as max$|S_{1,j}|$and max$|S_{4,j}|$in a given series of nominal values for p_j, were ranked in descending order. Other $S_{i,j}$ were not used in ranking the parameters. The sensitivity in positive direction, $p_j+\Delta p_j$ was reported as well as differences in bidirectional sensitivity above 0.005, $|S_{i,j}\,(p_j+\Delta p_j)-S_{i,j}\,(p_j-\Delta p_j)|$ > 0.005. If for given j and all $i \in [1{:}n_y]$, $|S_{i,j}|$<0.005 then the sensitivity coefficients were not reported.

Table 4.1 - Model parameter vector *P* used in sensitivity analysis. 'Type' indicates if a parameter p_j is of integer or real type, $E(p_j)$ gives the expected value of each p_j, p_j indicated with (+) in columns [*P'* DSA-test] and [*P"* MCA] were used in a linearity & superposability test, and in uncertainty analysis respectively. Parameter influence in model functions: 1) Plan jobs, 2) Execute job, 3) Task performance, 4) Report on task, 5) Resource use, 6) Define crop area, 7) Determine number of ripe roses.

Parameter description	Symbol	*j*	*P*	unit	Influence in function	Type	$E(p_j)$	*P'* DSA-test	*P"* MCA
Greenhouse management parameters									
Allowed number of harvest cycles per day	d_{hc}	1	P_m	d^{-1}	1, 2	I	2	-	-
Expected mean harvest capacity harvester	$E(C_o)$	2	P_m	h^{-1}	2, 5	R	500	+	-
Target process time harvest, k=1	$LT(n,k)$	3	P_m	h	2, 5	R	6.5	+	-
Greenhouse layout parameters									
Length greenhouse(length gutter)	L_{Gh}	4	P_g	m	6, 7	R	150	-	-
Number of spans per node(section)	n_{sp}	5	P_g	-	6, 7	I	3	-	-
Crop related parameter									
Yield(perturbation factor)	$Y_{n\,cf}$	6	P_c	-	7	R	1	-	-
Operator related parameters									
Trolley speed during task execution	v_o	7	P_o	m s^{-1}	2, 3, 5	R	0.39	+	+
Overlap distance 'move to rose' & 'cut rose'	D_o	8	P_o	m	3	R	0.5	+	+
μ in $LN(\mu, \sigma^2)$ of $p_v(T_{cr})$, cut rose	$\mu(T_{cr})$	9	P_o	s	3, 5	R	1.3054	+	+
σ in $LN(\mu, \sigma^2)$ of $p_v(T_{cr})$	$\sigma(T_{cr})$	10	P_o	s	3, 5	R	0.3608	+	+
μ in $LN(\mu, \sigma^2)$ of $p_v(T_{stb})$, store to buffer	$\mu(T_{stb})$	11	P_o	s	3, 5	R	-0.3955	+	+
σ in $LN(\mu, \sigma^2)$ of $p_v(T_{stb})$	$\sigma(T_{stb})$	12	P_o	s	3, 5	R	0.6622	+	+
μ in $LN(\mu, \sigma^2)$ of $p_v(T_{p1n})$, place 1 net	$\mu(T_{p1n})$	13	P_o	s	3, 5	R	2.4699	+	-
σ in $LN(\mu, \sigma^2)$ of $p_v(T_{p1n})$	$\sigma(T_{p1n})$	14	P_o	s	3, 5	R	0.4011	+	-
μ in $LN(\mu, \sigma^2)$ of $p_v(T_{p2n})$, place 2 nets	$\mu(T_{p2n})$	15	P_o	s	3, 5	R	3.4242	+	+
σ in $LN(\mu, \sigma^2)$ of $p_v(T_{p2n})$	$\sigma(T_{p2n})$	16	P_o	s	3, 5	R	0.1591	+	+
μ in $LN(\mu, \sigma^2)$ of $p_v(T_{t1n})$, time log 1 net	$\mu(T_{t1n})$	17	P_o	s	4	R	10	+	-
σ in $LN(\mu, \sigma^2)$ of $p_v(T_{t1n})$	$\sigma(T_{t1n})$	18	P_o	s	4	R	1	+	-
μ in $LN(\mu, \sigma^2)$ of $p_v(T_{t2n})$, time log 2 nets	$\mu(T_{t2n})$	19	P_o	s	4	R	15	+	-
σ in $LN(\mu, \sigma^2)$ of $p_v(T_{t2n})$	$\sigma(T_{t2n})$	20	P_o	s	4	R	1	+	-
μ in $LN(\mu, \sigma^2)$ of $p_v(T_{bb})$, bind bundle	$\mu(T_{bb})$	21	P_o	s	2, 3	R	2.9002	+	+
σ in $LN(\mu, \sigma^2)$ of $p_v(T_{bb})$	$\sigma(T_{bb})$	22	P_o	s	2, 3	R	0.3491	+	+

4.4.2 Uncertainty

For simulation of a given scenario, input uncertainty translates to variation in system performance vector *y*, also called output uncertainty. As the GWorkS-model is meant to find best scenarios, it is relevant to determine output uncertainty. Simulation output differences are not significant if output uncertainty ranges overlap. Monte Carlo analysis was used to estimate effects of uncertainty in input parameters on model output *y*. Lomas & Eppel (1992) state that above 60-80 simulations only marginal improvements in accuracy are obtained. To produce a reliable probability distribution for *y*, 100 simulations were chosen as a safe number (Fig. 4.2).

The parameter vector *P* was reduced to parameter vector *P”* by excluding the greenhouse layout parameters with negligible uncertainty (Table 4.1), management decision parameters (Table 4.1) and parameters with normalised sensitivity coefficient for labour time $|S_{1,j}| < 0.01$ as determined in Section 4.5.1 and 4.5.2. *P”* contains observed p_j. Elements of *P”* are indicated in Table 4.2. The probability distribution of $p_j \in P''$ was assumed Gaussian for all parameters and may thus be defined as $p_j=E(p_j) + \sigma(p_j)\,\xi$, where $E(p_j)$ is the expected mean, $\sigma(p_j)$ the standard deviation and ξ is a standard Gaussian random variable with μ=0 and σ=1 (Kim et al., 2007). Standard deviation $\sigma(p_j)$ was estimated from the 95% confidence interval boundaries for measured p_j. Both $E(p_j)$ and confidence interval $ci(p_j)$ were determined from video recordings in a greenhouse (Van ’t Ooster et al., 2014). Each p_j was sampled at the start of each simulation.

Table 4.2 - Parameter vector *P”* holding observed non-integer p_j with impact >0.01 for one or more key performance indicators. Expected value $E(p_j)$ and standard deviation $\sigma(p_j)$ estimated from the 95% confidence interval as determined from video recordings. *n* indicates the number of observations.

Description parameter p_j	*P”*	$E(p_j)$	$\sigma(p_j)$	n
Trolley speed	v_o	0.39	0.0834	24
Overlap distance	D_o	0.5	0.1670	1419
μ in $p_v(T_{cr})$, cut rose	$\mu(T_{cr})$	1.3122	0.0084	1517
σ in $p_v(T_{cr})$	$\sigma(T_{cr})$	0.3330	0.0059	1517
μ in $p_v(T_{stb})$, store to buffer	$\mu(T_{stb})$	-0.3470	0.0261	496
σ in $p_v(T_{stb})$	$\sigma(T_{stb})$	0.5921	0.0185	496
μ in $p_v(T_{p2n})$, place 2 nets	$\mu(T_{p2n})$	3.4258	0.0465	13
σ in $p_v(T_{p2n})$	$\sigma(T_{p2n})$	0.1539	0.0359	13
μ in $p_v(T_{bb})$, bind buffer net	$\mu(T_{bb})$	2.9155	0.0496	35
σ in $p_v(T_{bb})$	$\sigma(T_{bb})$	0.2887	0.0362	35

The simulations covered one day with yield Y_n=1.6 stems m^{-2} and two harvest cycles with 2467 and 414 harvested stems. For the purpose of using MCA results in verification of DSA results (Section 4.4.3), a small model restriction was applied. The number of stems per subnode was sampled once and kept unchanged in successive simulations to prevent undesired yield effects from sampling of the probability density function on number of stems per subnode. The spatial distribution of ripe stems and stochastic service times of basic actions were re-sampled each simulation.

4.4.3 Verifying DSA using MCA

Total sensitivity in DSA is defined according to Lomas and Eppel (1992):

$$\Delta y_{i,tot} = \left(\sum_{j=1}^{n_p} \Delta y_{i,j}^{\,2} \right)^{1/2} \tag{2}$$

Where $\Delta y_{i,j}$ is the individual sensitivity of y_i for $p_j \in P''$ and n_p is the number of parameters. Total sensitivity Eq. (2) was determined for both 1% perturbation and $2.33\sigma(p_j)$ perturbation. Eq. (2) assumes that the sensitivity to each individual input is independent of other inputs and that the sensitivity is linear in the inputs. This necessary superposability constraint was tested in a combined linearity and superposability test for 1% parameter perturbation in P' (DSA-test, Table 4.1) by adding the individual input parameter sensitivities $\Delta y_{i,j}$ and comparing the result with a single simulation where all parameters are perturbed simultaneously. The sign of Δp_j is selected such that $\Delta y_{i,j}$ is of equal sign for all Δp_j. If the results are virtually identical, the system is considered superposable and Eq. (2) is valid.

In MCA, provided there are many inputs and irrespective of their individual distributions, predicted single outputs y_i are likely to be normally distributed (Lomas & Eppel, 1992). Assuming normally distributed outputs y_i and N Monte Carlo simulations, total sensitivity $\Delta y_{i,tot}$ is calculated according to Lomas & Eppel (1992):

$$\Delta y_{i,tot} = 2.33 \left[\frac{1}{N-1} \sum_{n=1}^{N} \left(y_{i,n}^2 - \bar{y}_i^{\,2} \right) \right]^{1/2} \tag{3}$$

Where $y_{i,n}$ is output y_i in simulation n, $\bar{y}_i$ is the mean of $y_{i,n}$ over N simulations. Eq. (3) represents the 99% probability range for the model output. The use of Eq. (3) is appropriate if the distribution of $y_{i,n}$ is not skewed.

Total sensitivity determined from Eq. (2) and Eq. (3) must be equal for linear and superposable systems (Lomas & Eppel, 1992). To verify this, total sensitivity $\Delta y_{i,tot}$ (DSA) and $\Delta y_{i,tot}$ (MCA) were compared. For $\Delta y_{i,tot}$ (DSA) the Δp_j were chosen equal to $2.33\sigma(p_j)$. The standard deviation $\sigma(p_j)$ is given in Table 4.2. If total sensitivity of model output for DSA (Eq. (2)), matches the 99% confidence interval of model output using MCA (Eq. (3)), then both methods agree for parameter perturbation of $2.33\sigma(p_j)$. The $2.33\sigma(p_j)$ perturbation is greater than the 1% perturbation for all $p_j \in P''$. Acceptability of DSA as a method for use with the stochastic GWorkS-model is in that case highly probable, but not certain since validity of individual sensitivity $\Delta y_{i,j}$ cannot be proven this way.

4.5 Results and discussion specific sensitivity analysis

Results on the sensitivity analysis of harvest operations in static rose cultivation system are presented and discussed in view of the 3 research aims given in Section 4.2. These are, relevance of inputs and importance of accuracy in measured parameters, features of the growing system and implications for design, and model ability to discriminate between scenarios. Section 4.5.1 and 4.5.2 report the relevance of inputs based on individual sensitivity analysis using DSA. Section 4.5.1 presents the normalised sensitivity coefficients $S_{i,j}$ of model outputs for parameter vector P, at mean yield and perturbation factor 0.01. Section 4.5.2 reports individual sensitivity of harvest labour time T_T, $S_{1,j}$, at 5 yield levels Y_n. Section 4.5.4 reports output uncertainty using MCA.

4.5.1 Individual sensitivity at mean yield

The individual sensitivity of the model performance at mean daily yield (1.6 stems m^{-2}) and one harvest cycle is presented in Table 4.3. All elements of parameter vector P, Table 4.1, were used for DSA. Parameters with $S_{i,j}$ < 0.005 for all performance indicators were not presented. Normalised sensitivity coefficients $S_{i,j}$ were sorted based on the impact on labour time T_T $(i=1)$. At given Y_n one harvester is active and thus for operator parameters P_o, the values of $S_{i,j}$ for labour time T_T and subnode cycle time $CT_{sn}(1)$ are essentially equal.

The management parameters P_m with exception of d_{hc} are not in Table 4.3 since a 1% perturbation was insufficient to create an effect. The parameters ‘expected average harvest rate’ $E(C_o)$ and ‘target lead time in node n for harvest’ $LT(n,k)$, k=1, are used in the job planner (Fig. 4.1) to assign 1, 2 or 3 harvesters to a section, a stair function. A 1% change in either one of these two parameters does not affect the number of harvesters assigned to a greenhouse section. For integer parameter, decision number of harvest cycles d_{hc}, $S_{i,1}$ was determined using Δp_j=1. Implementing two harvest cycles instead of one has a negative effect on most performance indicators, labour time T_T increases ($S_{1,1}$=0.16), throughput TH decreases ($S_{4,1}$= –0.30), transport distance D_T ($S_{9,1}$=0.74) and time T_{Tt} ($S_{11,1}$=0.86) increase and the number of rose nets delivered N_{rnd} increase ($S_{14,1}$=0.13). Transport time and distance increase less than proportionally, since less rose nets are handled per cycle. The cycle time per rose bed in harvest cycle 1 decreases ($S_{7,1}$= –0.21) and overlap time T_{To} increases ($S_{13,1}$=0.34) because of lower ripe stem density per cycle.

The impact resulting from greenhouse length L_{Gh} on labour time T_T is amongst the highest ($S_{1,4}$=0.75), however as a result of a change in greenhouse section dimensions, parameters in P_g also affect crop area and thus the amount of stems harvested at constant Y_n (stems m^{-2}).

This makes impact of P_g on T_T less interesting since it does not directly point to labour efficiency increase. Throughput *TH* shows a much lower sensitivity to L_{Gh} ($S_{4,4}$=0.24 for +Δp_j and $S_{4,4}$=-0.05 for -Δp_j) than labour time ($S_{1,4}$=0.75). So, for parameters with an effect on harvested stems and no effect on number of harvesters, throughput *TH* is a better indicator for labour efficiency than is total labour time $T_{T,}$ as throughput compensates for yield effects. $S_{4,4}$ differs for +Δp_j and -Δp_j as a result of stochastic redistribution of ripe stems along the path. Changing the integer parameter greenhouse section width n_{sp} from 3 (12m) to 2 spans (8m) results in normalised sensitivity coefficients close to 1 for labour time and its components cut time T_{Tc}, transport time T_{Tt} and overlap time as well as for transport distance D_T. This is predominantly a yield effect as throughput *TH* ($S_{4,5}$= –0.01) and cycle time per subnode $CT_{sn}(1)$ ($S_{7,5}$= –0.04) show.

Table 4.3 - Normalised sensitivity coefficients $S_{i,j}$ of model performance indicators at mean daily yield (1.6 stems m^{-2}) and one harvest cycle for all model parameters *P*. Parameters p_j with $|S_{i,j}|$ < 0.005 for all y_i were omitted. A blank indicates $|S_{i,j}|$ < 0.005. Absolute $S_{i,j}$ difference above 0.005 for perturbation +Δp_j and -Δp_j is indicated bold. T_T is total daily labour time (h), *TH* is product throughput (s^{-1}), D_T is operator transport distance (m), T_{Tc} is cumulative cut time (h), T_{Tt} is cumulative transport time (h), T_{To} is cumulative overlap time moving-cutting (h), and $CT_{sn}(1)$ is cycle time per rose bed in harvest cycle 1.

Description	$p_j \in P$	*j*	*Class*	T_T	*TH*	D_T	T_{Tc}	T_{Tt}	T_{To}	$CT_{sn}(1)$
		⮟	*i* ➤	1	4	9	10	11	13	7
Spans per section	n_{sp}	5	P_g	0.98	-0.01	1.06	0.97	1.03	1.03	-0.04
μ of pdf cut rose	$\mu(T_{cr})$	9	P_o	**0.91**	-0.90		**1.09**			**0.92**
Length greenhouse	L_{Gh}	4	P_g	**0.73**	**0.24**	**0.80**	**0.96**	**0.91**	**1.91**	**0.76**
Yield gain factor	$Y_{n\,cf}$	6	P_c	**0.62**	**0.37**	**-0.05**	**0.96**	**-0.04**	**1.27**	**0.62**
Harvest cycles a day	d_{hc}	1	P_m	0.16	-0.30	0.74		0.86	0.34	-0.21
Trolley speed	v_o	7	P_o	-0.11	0.11			**-0.91**	**-0.83**	-0.11
σ of pdf cut rose	$\sigma(T_{cr})$	10	P_o	0.10	-0.10		0.11			0.10
μ of pdf bind bundle	$\mu(T_{bb})$	21	P_o	0.07	-0.07					0.07
μ of pdf place 2 nets	$\mu(T_{p2n})$	15	P_o	0.07	-0.07					0.07
Overlap distance	D_o	8	P_o	-0.06	0.06				0.31	-0.06
σ of pdf store to buffer	$\sigma(T_{stb})$	12	P_o	0.06	-0.06		0.07		0.02	0.06
μ of pdf store to buffer	$\mu(T_{stb})$	11	P_o	-0.04	0.04		-0.07		-0.06	-0.04
μ of pdf time log 2 nets	$\mu(T_{t2n})$	19	P_o	0.01	-0.01					0.01

The routing in a greenhouse section is pre-set and therefore walk distance D_T is only affected by parameters changing path length, pass through frequency and or harvested stems, d_{hc}, n_{sp}, L_{Gh}, and $Y_{n\,cf}$. Operator-related parameters P_o have no impact on D_T.

Several operator parameters $p_j \in P_o$ show a clear impact on labour time T_T. All operator parameters except $\mu(T_{cr})$ have equal impact on throughput *TH* and T_T but reversed in sign, thus proving a direct effect on labour efficiency. The parameters of the probability distribution function for a 'cut rose' action, $\mu(T_{cr})$ and $\sigma(T_{cr})$, have most impact on T_T, respectively $S_{1,9}$=0.91

and $S_{1,10}$=0.10 and obviously even higher impact on cut time itself T_{Tc}, respectively $S_{10,9}$=1.09 and $S_{10,10}$=0.11. Trolley speed v_o is the next most important: if v_o increases, T_T decreases ($S_{1,7}$= –0.11). Trolley speed directly affects the labour time components transport T_{Tt} ($S_{11,7}$= –0.91) and overlap T_{To} ($S_{13,7}$= –0.83). Though both sensitivity coefficients are negative they have a counteractive effect and a limited share in total labour time T_T, which results in a much lower impact of v_o on T_T and TH. Better anticipation induces earlier start of a rose cut action, increases overlap distance D_o, and decreases labour time T_T ($S_{1,8}$= –0.06). The impact of the action 'buffer rose', $\mu(T_{stb})$ and $\sigma(T_{stb})$, is low since it is executed simultaneously with transport. The less frequent actions 'bind roses in net' $p_v(T_{bb})$, 'place 2 nets in trolley' $p_v(T_{p2n})$, and 'time-log 2 empty rose nets' $p_v(T_{t2n})$ show low impact, ranging from 0.07 to –0.04 for probability density function parameter μ.

Perturbation in yield Y_n was defined by means of gain factor $Y_{n\ cf}$. Overlap time T_{To} was most sensitive for $Y_{n\ cf}$ ($S_{13,6}$=1.27) as a result of each stem contributing to overlap time and an unwanted model effect resulting from stochastic repositioning of stems. With increased yield Y_n, cut time T_{Tc} increases ($S_{10,6}$=0.96), labour time T_T and throughput TH increase with $S_{1,6}$=0.62 and $S_{4,6}$=0.37 respectively, and transport distance D_T and time T_{Tt} are left almost unaffected with $S_{9,6}$= –0.05 and $S_{11,6}$= –0.04 respectively. The sensitivity coefficient for cut time is almost 1 as the number of cut actions and yield Y_n are proportional. Labour time and throughput sensitivity are less than 1, because these performance indicators aggregate all actions in the greenhouse section. Throughput sensitivity is less than labour time sensitivity because throughput is a ratio between node cycle time and number of stems harvested. Throughput is affected by random repositioning of stems in case of change in Y_n. The sensitivity coefficients for D_T and T_{Tt} are negative because rose nets were unloaded from positions closer to the main buffer.

In addition, to verify if DSA result is affected by the use of 'frozen' random number series, 30 replications of the full DSA procedure were executed with different random seeds. Results not shown. These replications showed a maximum standard deviation in $S_{i,j}$ of less than 0.01 for parameters which have no yield effect and 1.1 for parameters with a yield effect. In the last group, SD($S_{13,j}$) for overlap time is highest.

Overall, at mean daily yield, the model is not extremely sensitive ($|S_{i,j}|$>>1) for the parameters tested. As throughput TH compensates for yield effects, it is a better indicator for labour efficiency at a constant number of operators. Parameters with $|S_{i,j}|\geq$0.1 in labour time T_T or throughput TH must be chosen with care. In descending order, for labour time these are n_{sp}, $\mu(T_{cr})$, L_{Gh}, $Y_{n\ cf}$, d_{hc}, v_o, and $\sigma(T_{cr})$ and for throughput $\mu(T_{cr})$, $Y_{n\ cf}$, d_{hc}, L_{Gh}, v_o, and $\sigma(T_{cr})$. Parameters causing low sensitivity, 0.01$\leq|S_{i,j}|$<0.1 in labour time T_T or throughput TH, are in descending order $\mu(T_{bb})$, μ (T_{p2n}), D_o, $\sigma(T_{stb})$, $\mu(T_{stb})$, and $\mu(T_{t2n})$. Parameters not needing accurate specification ($|S_{i,j}|< 0.01$) are seven operator parameters and two management parameters. The operator parameters define probability density functions of actions in parallel execution, e.g. store rose to trolley buffer T_{stb} executed in parallel with move along path, and probability density functions of low frequent actions on handling of rose nets, e.g. time log nets (T_{t1n}, T_{t2n}), place nets in trolley (T_{p1n}, T_{p2n}), and bind filled nets (T_{bb}). Parameters with very low sensitivity are $\sigma(T_{p2n})$, $\sigma(T_{bb})$, and $\sigma(T_{t2n})$. The value of $S_{i,j}$=0 for $\mu(T_{t1n})$, $\sigma(T_{t1n})$, $\mu(T_{p1n})$, and $\sigma(T_{p1n})$, since the simulation did not apply single rose net operations (T_{t1n}, T_{p1n}). Also $S_{i,j}$=0 for management parameters $E(C_o)$ and $LT(L,k)$ for reason that a 1% perturbation did not affect resource use.

4.5.2 Individual sensitivity of labour time at five yield levels

Harvest labour time in a practical greenhouse is highly affected by daily yield Y_n and the decision to harvest once or twice a day. Therefore, it was determined how Y_n and the number of harvest cycles affect the normalised sensitivity coefficients for labour time, $S_{1,j}$. Fig. 4.3 presents parameters with the highest positive impact on labour time, it shows generally that $S_{1,j}$ increases with yield.

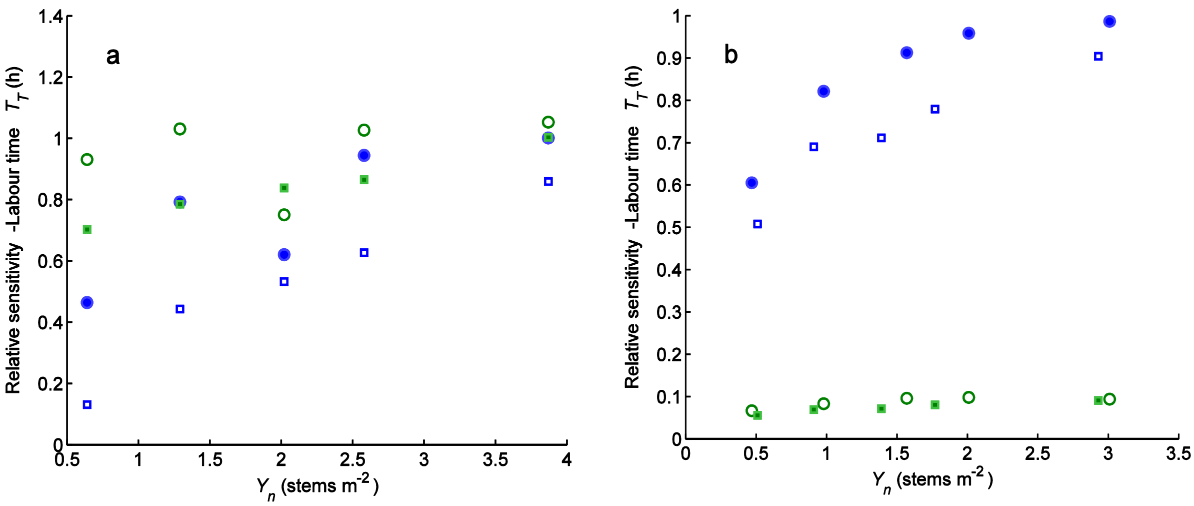

Fig. 4.3 - Normalised sensitivity coefficients $S_{1,j}$ for labour time T_T at 5 yield levels Y_n with one and two harvest cycles (1hc & 2hc), $p_j \in P$ with direct impact (a) and without impact (b) on number of stems harvested for which T_T is most sensitive, $\max|S_{1,j}| \geq 0.1$. a) $p_j \in [Y_{N\,cf}, L_{gh}]$: Yield perturbation (-), $p_6 = Y_{N\,cf}$, at 1hc (●) and 2hc (□), greenhouse length (m), $p_4 = L_{gh}$, at 1hc (○) and 2hc (■). b) $p_j \in [\mu(T_{cr}), \sigma(T_{cr})]$: mean of cut times natural logarithm, $p_9 = \mu(T_{cr})$, at 1hc (●) and 2hc (□), standard deviation of cut times natural logarithm, $p_{10} = \sigma(T_{cr})$, at 1hc (○) and 2hc (■).

Fig. 4.3a shows $S_{1,j}$ for parameters yield gain $Y_{N\,cf}$ and greenhouse length L_{Gh}, which affect the number of stems harvested. Yield gain $Y_{N\,cf}$, a multiplier for Y_n, brings an immediate change in the yield Y_n. At given Y_n (stems m^{-2}), a change in L_{Gh} results in change of crop area and of number of harvested roses. Because of this yield effect, each run results in different positioning of ripe roses on gutters. For yield gain $Y_{N\ cf}$, $S_{1,6}$ increases with yield. This is caused by an increased time share for stem handling in total labour time. This time share rises from 55% at low yield to 91% at high yield for 1 harvest cycle, and from 47% to 83% for 2 harvest cycles, overlap time T_{To} effects excluded (not presented). Labour time sensitivity for greenhouse length L_{Gh} is higher than for yield gain $Y_{N\ cf}$ because greenhouse length affects all actions, e.g. not only number of harvested stems but also transport distance. Both for $Y_{N\ cf}$ and L_{Gh} and one harvest cycle per day a change in trend occurs at Y_n=2 stems m^{-2}. At this point sensitivity coefficient $S_{1,j}$ is relatively low because compared to other yield levels, perturbation in T_T (=Δy_1) is relatively small. This is mainly caused by high sensitivity of parallel processing at this yield point: $S_{13,j}$ of overlap time T_{To} for L_{Gh} and $Y_{N\ cf}$ are 1.91 and 1.27 respectively (Table 4.3) as opposed to 0.97 and 0.48 respectively at Y_n=1.29 and 0.34 and –0.38 at Y_n=2.58. Parallel processing is affected by number of harvested stems and expected distance between harvested roses $E(D_s)$. Overlap time T_{To} increases with number of harvested stems, but overlap time per stem decreases when $E(D_s) < D_o + v_oE(T_{stb})$. The last effect is strongest at Y_n=2 stems m^{-2}.

Fig. 4.3b presents $\mu(T_{cr})$ and $\sigma(T_{cr})$ in LN(μ,σ^2) for the action 'cut rose'. With yield, labour time sensitivity for $\mu(T_{cr})$ increases non-linearly from 0.6 to almost 1 as the time share for cutting, T_{Tc} over T_T, increases with yield. The effect is not linear due to a decreasing relative time demand for actions other than cutting stems and a decreasing overlap time per stem (not presented). With two harvest cycles, $S_{1,j}$ represents the effect of both harvest cycles in T_T. $S_{1,j}$ increase with yield is smaller with two than with one harvest cycle, because of a lower ripe stem density per cycle, more transport, and thus lower time shares for cut actions. At low yield and two cycles (2hc), the effect of high trolley speed in cycle 2 is illustrated. For a daily yield Y_n of 0.5 and 1 stems m^{-2}, trolley speed is 1 m s^{-1}. This results in less time benefit from parallel execution of the actions 'move along path' and 'cut rose' and more impact of $\mu(T_{cr})$ itself on T_T. Fig. 4.3b also shows that sensitivity of T_T for $\sigma(T_{cr})$ is small compared to the sensitivity for $\mu(T_{cr})$. For one harvest cycle, $S_{1,10}$ increases from 0.07 at 0.5 stems m^{-2} to a maximum of 0.10 at 2 stems m^{-2}. Parallel moving and cutting works as a cut-off filter for low cut time samples. With increased $\sigma(T_{cr})$, the higher probability for low cut times shows effect because of less overlap at higher yield, thus decreasing $S_{i,j}$ for Y_n > 2 stems m^{-2}. No maximum shows when Y_n is harvested in two cycles as the overlap effect is less.

Fig. 4.4a shows the impact of trolley speed v_o and overlap distance D_o. Both are negative and $S_{1,j}$ decreases with yield. At mean yield (Y_n=1.6) a 1% trolley speed increase results in 0.11% labour time decrease ($S_{1,7}$= –0.11), at low yield $S_{1,7}$= –0.45 and at high yield $S_{1,7}$= –0.03. This decreasing sensitivity is a combined result of a decreasing time share of transport time T_{Tt} in T_T and a decreasing effect of time overlap T_{To} benefits. With two harvest cycles absolute impact of trolley speed is higher as a result of more transport, however at Y_n is 0.5 and 1 stems m^{-2} $S_{1,7}$ is decreased because it does not include effects of high trolley speed since base trolley speed was the parameter investigated. Earlier anticipation on a ripe stem, D_o in Fig. 4.4a, decreases labour time T_T. For one harvest cycle $S_{1,8}$= –0.1 at low yield and $S_{1,8}$= –0.02 at high yield. $S_{1,8}$ decreases non-linear with yield as a result of increasing probability of finding a next stem within the anticipation range. With two harvest cycles, D_o increase has a higher, more negative impact on labour time T_T since the distance between ripe stems is higher. At low yield and two harvest cycles, trolley speed is 1 m s^{-1}, thus less time is available during D_o and the effect in T_T is smaller as the lower $S_{1,8}$ values show.

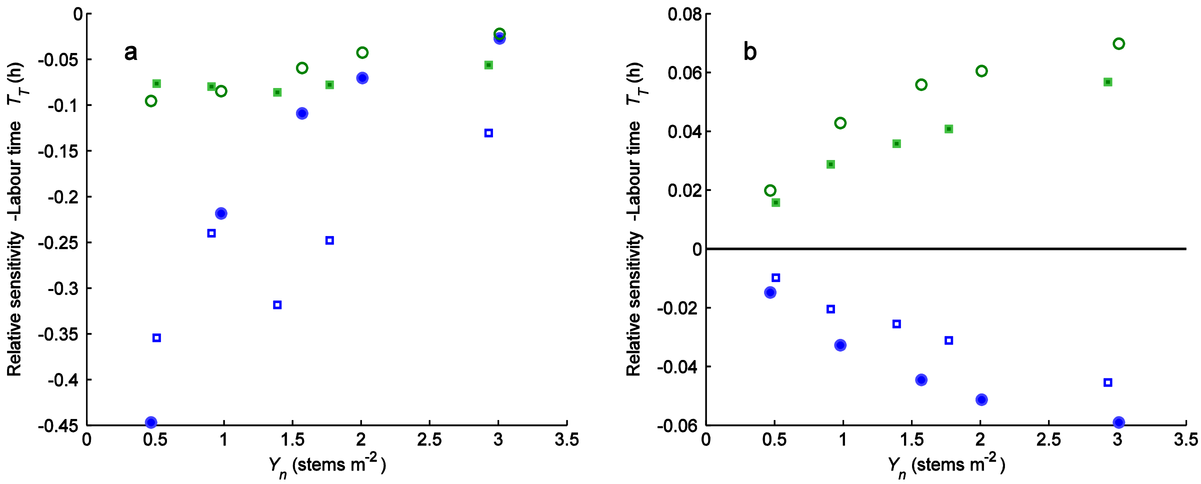

Fig. 4.4 - Normalised sensitivity coefficients $S_{1,j}$ for labour time T_T at 5 yield levels Y_n with one and two harvest cycles (1hc & 2hc), $p_j \in P$ for which T_T has a negative $S_{1,j}$ and max$|S_{1,j}| \geq 0.1$ (a), and $p_j \in P$ for which T_T is low sensitive, with $0.01 \leq$ max$|S_{1,j}| < 0.1$ (b). (a) $p_j \in [v_o, D_o]$: operator velocity at task operation (m s^{-1}), $p_7 = v_o$, at 1hc (●) and 2hc (□), overlap distance move and rose cut action (m), $p_8 = D_o$, at 1hc (○) and 2hc (▣). (b) $p_j \in [\mu(T_{stb}), \sigma(T_{stb})]$: mean and standard deviation of store to buffer time's natural logarithm. Mean $p_{11} = \mu(T_{stb})$ at 1hc (●) and 2hc (□), standard deviation $p_{12} = \sigma(T_{stb})$ at 1hc (○) and 2hc (▣).

Fig. 4.4b presents $\mu(T_{stb})$ and $\sigma(T_{stb})$ in LN(μ,σ^2) for the action 'store stem to trolley buffer'. This action is fast and executed simultaneously with the action 'move to (next) rose'. Sensitivity of labour time for these parameters is increasing with yield because the time overlap per stem decreases with increasing density of ripe stems. The apparent negative impact of $\mu(T_{stb})$ is a result of negative nominal $\mu(T_{stb})$. The effect of $\sigma(T_{stb})$ is similar to that of $\mu(T_{stb})$. Higher $\sigma(T_{stb})$ increases probability for higher T_{stb} samples and the probability to be in parallel action execution is less at higher T_{stb} thus leading to an increase in T_T. With two harvest cycles, the impact of $\mu(T_{stb})$ and $\sigma(T_{stb})$ is less for reasons given.

4.5.3 Summarized sensitivity results

Overall, impact of yield is high and labour time sensitivity for all parameters $p_j \in P$ changes with yield with the highest $S_{1,j}$ close to 1. When measured yield data are not available for comparative simulations, crop models might be used for yield prediction (Buck-Sorlin et al., 2011). Parameters affecting absolute yield inevitably produce output that is not fully deterministic since it requires resampling of the stochastic number of stems in each subnode and stochastic redistribution of ripe stems to gutter positions. Also, the management decision ‘number of harvest cycles’ has a clear impact on the individual sensitivity of labour time.

With respect to the objective “identify parameter importance for model prediction”, labour time is classified as sensitive, $\max|S_{1,j}|\geq 0.1$, for greenhouse length L_{Gh}, operator cutting performance $p_v(T_{cr})$, trolley speed v_o, and anticipation distance D_o. Labour time is classified as low sensitive, $0.01\leq\max|S_{1,j}|<0.1$, for ‘store to buffer’ performance $p_v(T_{stb})$ and for μs of low frequent operator actions on rose nets. $S_{1,j}$ ranges from 0.035 to 0.075 for $\mu(T_{bb})$ and $\mu(T_{p2n})$, for other μs ($\mu(T_{p1n})$, $\mu(T_{p1n})$, and $\mu(T_{t2n})$) $S_{1,j}$ <0.02. Labour time is insensitive for σ's of these low frequent operator actions with $S_{1,j}$<0.005 for all yield levels. It does not harm the model prediction ability if these parameters are only roughly estimated or if the model is simplified at this point.

With respect to the objective “identify growing system features that could guide designer and grower to an improved system design”, first focus must be on technical aids or system modifications that reduce $\mu(T_{cr})$ because of high impact on labour time (Fig. 4.3b). Second, expose ripe roses to allow early and reliable anticipation for cutting a next rose while moving in the path (high D_o), higher operator velocity v_o, and a narrow probability distribution for $p_v(T_{cr})$ with low $E(T_{cr})$ (Table 4.3, Figs. 3b and 4a). Third, throughput would benefit from preventing a 2nd harvest cycle (Table 4.3), however this decision is crop and climate dependent. Product quality effects dominate this decision and need further investigation. Fourth, couple trolley speed and yield which sorts biggest effect at yields under 2 stems m^{-2} (Table 4.3, Fig. 4.4a).

4.5.4 Uncertainty analysis using MCA

At mean yield level, key performance indicator uncertainty was determined based on uncertainty in parameter vector *P”* (Table 4.2). The Monte Carlo simulation results are given in Table 4.4.

Table 4.4 - Monte Carlo analysis result based on uncertainty in *P"*, 100 day simulations, one greenhouse section, and Y_n=1.6 stems m^{-2}. The uncertainty of performance indicators is assumed normally distributed and represented by its mean and coefficient of variation (CV). ci mean and ci SD indicate the 95% confidence interval for mean and standard deviation.

Performance indicator	y_i	unit	mean	CV (%)	ci mean	ci SD
Harvest labour time	T_T	h	5.090	4.8	$\pm$0.048	0.214-0.283
Utilisation operator 1	$u_o(1)$	-	0.636	4.8	$\pm$0.006	0.027-0.035
Throughput	TH	st. s^{-1}	0.158	4.5	$\pm$0.001	0.006-0.008
Distance travelled	D_T	m	4134	0.0	$\pm$0	0
Accumulated cut time	T_{Tc}	h	3.823	1.0	$\pm$0.007	0.032-0.042
Acc. transport time	T_{Tt}	h	1.919	18.0	$\pm$0.069	0.303-0.401
Acc. overlap time	T_{To}	h	0.925	19.6	$\pm$0.036	0.159-0.211
Cycle time 1 path side	$CT_{sn}(1)$	s	612	5.8	$\pm$7	31-41
Cycle time 1 path side	$CT_{sn}(2)$	s	140	1.7	$\pm$0.466	2-3
Rose nets delivered	N_{rnd}	-	23	0	$\pm$23	0

Uncertainty is most notable in transport time T_{Tt} and overlap time T_{To} with coefficients of variation CV of 18 and 19.6%. These model outputs are directly affected by trolley speed v_o and overlap distance D_o, the parameters with the highest uncertainty (Table 4.2). The number of rose nets delivered N_{rnd} is not affected by parameter uncertainty, therefore total distance D_T is also not affected. Cut action time T_{Tc} is hardly affected by input uncertainty (CV= 1%). For labour time T_T, throughput TH, and utilisation of the harvester $u_o(1)$, CV is close to 5%. Since one harvester was active, $u_o(2)$=0 and uncertainty in node cycle time CT_n (not presented) is equal to that in labour time T_T. As a result of low yield in harvest cycle two, the trolley runs at maximum speed, which was not subjected to uncertainty analysis. A lower uncertainty for the cycle time per rose bed CT_{sn} in harvest cycle two (CV= 1.7%) compared that in harvest cycle one (CV= 5.8%) resulted. The confidence intervals of the mean and standard deviation of labour time and throughput are small.

With respect to the third objective, the parameters v_o and D_o are the main cause of uncertainty. Reduction of uncertainty for D_o and v_o would further improve the ability of the model to discriminate between alternative scenarios.

4.6 Results and discussion methodology

Since DSA can only be applied if the method is valid for use with the GWorkS model, the application of the DSA method is verified in this Section. Section 4.6.1 presents the results of the linearity and superposability test and Section 4.6.2 reports total sensitivity as a verification of application of DSA.

4.6.1 Linearity and superposability test

All parameters without a parameter dependent absolute yield effect, indicated as in *P'* in Table 4.1, were included in a linearity and superposability test at a 1% perturbation. In Fig. 4.5 the results are given for y_i, i=[1, 10, 11, 13] being harvest labour time T_T and its main components T_{Tc}, T_{Tt} and T_{To}. Though Δy_i is small, Fig. 4.5 clearly shows that the lines representing the linear sum of individual sensitivity, $y_i + \sum_{P'} \Delta y_{i,j}$, match the lines resulting from simultaneous perturbation of all $p_j \in P'$, $y_i + \Delta y_i$ (P_p'). A similar result was found for throughput *TH*, node cycle time CT_n, operator utilisation u_o, and distance travelled D_T. This means that parameter impacts are independent, the system is superposable and Eq. (2) applicable for small parameter perturbations.

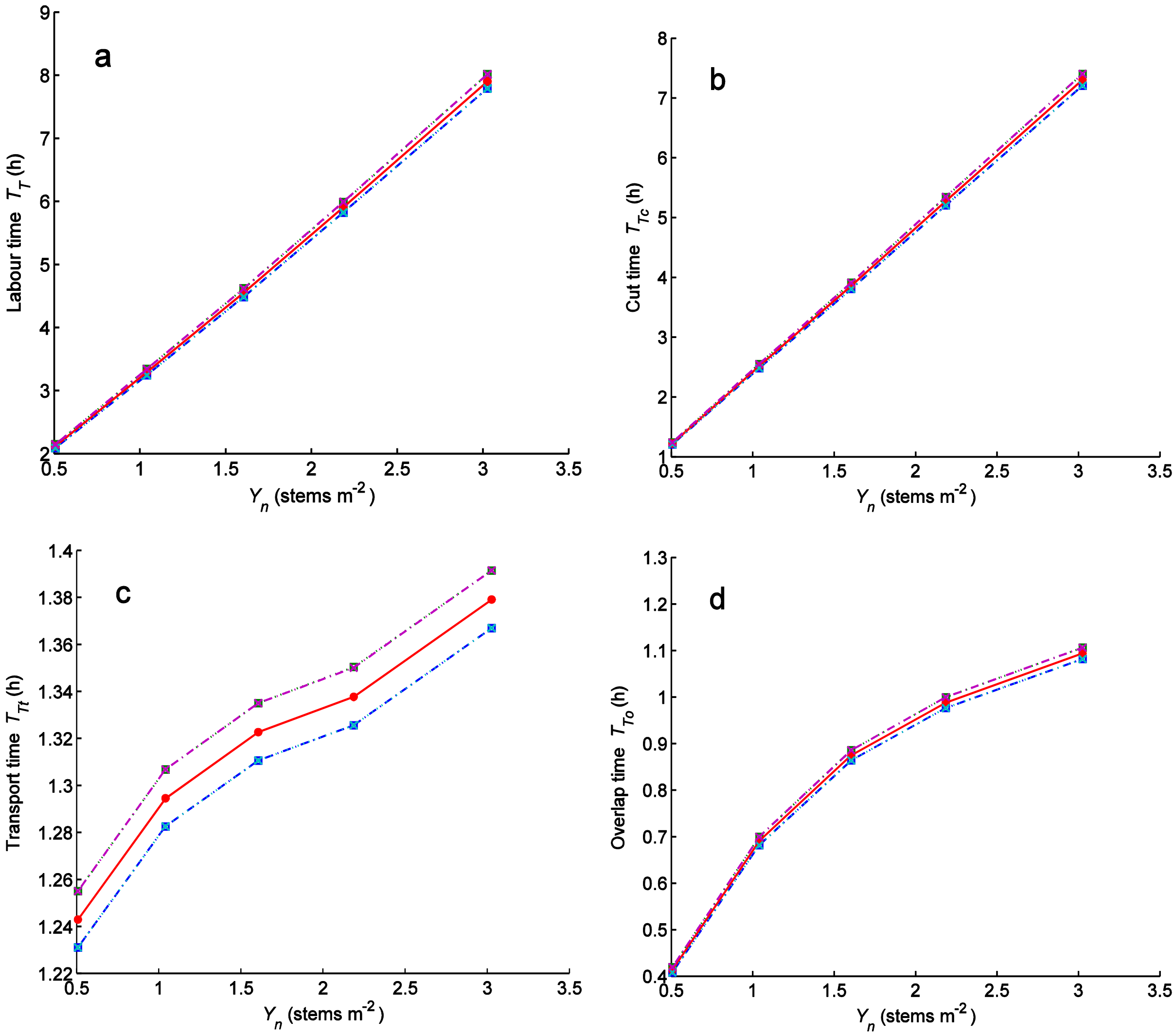

Fig. 4.5 - Linearity and superposability test result on a 1% perturbation of $P' \in P$ for labour time T_T (a) and its main components cut time T_{Tc} (b), transport time T_{Tt} (c), and action overlap time T_{To} (d). *P'* is defined in Table 4.1. Curves for simultaneous perturbation of all $p_j \in P'$ for negative Δy_i ( ) or positive Δy_i ( ), curves for linear sum of individual sensitivity $\Delta y_{i,j}$ for each $p_j \in P'$ sorted for negative ( ) or positive ( ) contribution to Δy_i, and nominal curves with y_i ( ).

In a first linearity test, it was tested whether the single-parameter perturbation $+\Delta p_j$ and $-\Delta p_j$ show equal change in y_i but opposite in sign. In Table 4.3 the bold numbers indicate different y_i-gradient for $+\Delta p_j$ and $-\Delta p_j$. Non-linearity is apparent for parameters with an effect on absolute yield (stems). In a second linearity test, it was tested whether the model shows linear response to simultaneous perturbation of parameters with positive output effect $+\Delta y_i$ and to those with a negative output effect $-\Delta y_i$. For parameter vector *P′,* linearity is proven since the distance of the upper curves in Fig. 4.5 from the nominal curves is equal to that of the lower curves. This means that for small perturbations in *P′* the model behaves as a linear system in its response to $\Delta P'$ at each Y_n level. So, for small perturbations of parameters without a direct absolute yield effect, the model may be considered linear and superposable. This means that the GWorkS-rose model meets the basic constraints as defined by Lomas and Eppel (1992) for application of DSA in individual as well as in total sensitivity analysis.

4.6.2 DSA verification result

Total sensitivity was determined using Eqs. (2) and (3) for parameter perturbation equal to input uncertainty. Comparison of total sensitivity $\Delta y_{i,tot}$ for MCA and DSA under the assumption of normally distributed output in Table 4.5 shows that uncertainty order of magnitude is the same when represented by the average of $-\Delta y_{i,tot}$ and $+\Delta y_{i,tot}$. Closer investigation of the DSA result showed considerable difference between total uncertainty for $-\Delta P''$ and $+\Delta P''$. The ratio $-\Delta y_{i,tot}/+\Delta y_{i,tot}$ ranged from 1.1 for $CT_{sn}(2)$ to 3.0 for transport time T_{Tt}, meaning that model linearity is lost at larger perturbations in *P″*. Also, superposability is less clear than with small perturbations in *P″*. For MCA, descriptive statistics on the 100 Monte Carlo simulations showed that all resulting performance indicator distributions were significantly skewed with exception of cut time T_{Tc} and subnode cycle time $CT_{sn}(2)$. Skewness ranged from 0.64 to 1.3. This makes the 2.33*SD* uncertainty bounds defined in Eq. (2) and (3) less appropriate. As an alternative for MCA the upper and lower bound may be defined by the values exceeded by 1 Monte Carlo simulation only. In Table 4.5, this MCA interval [$\Delta y_{i,tot}$ range (MCA)] was compared to the DSA total sensitivity interval [$\Delta y_{i,tot}$ range (DSA)], calculated based on Eq. (2) but with parameter perturbations grouped for a positive output effect $+\Delta y_i$ and for a negative output effect $-\Delta y_i$.

Table 4.5 - Comparison of total sensitivity $\Delta y_{i,tot}$ according to MCA and DSA based on 1) the assumption of normally distributed output and 2) the 99% bounds of the uncertainty range. '$\Delta y_{i,tot}$ range' is the uncertainty range with 1% probability outside the range for MCA and sorted parameter contribution to Δy_i for DSA. $\overline{y_i}$ is the mean performance indicator value based on 100 simulations.

Performance indicator			Assumed normally distributed output		Alternative: Use of upper and lower probability distribution bounds			
			MCA	DSA	MCA		DSA	
	y_i	Unit	$\Delta y_{i,tot}$	$\Delta y_{i,tot}$	$\overline{y}_i$	$\Delta y_{i,tot}$ range	y_i nom	$\Delta y_{i,tot}$ range
Harvest labour time	T_T	h	0.568	0.476	5.090	4.771 - 5.840	5.072	4.793 - 5.745
Utilisation operator 1	$u_o(1)$	-	0.071	0.059	0.636	0.596 - 0.730	0.634	0.599 - 0.718
Throughput	TH	stems s^{-1}	0.017	0.013	0.158	0.137 - 0.168	0.158	0.140 - 0.167
Acc. cut time	T_{Tc}	h	0.085	0.086	3.823	3.745 - 3.913	3.846	3.753 - 3.926
Acc. transport time	T_{Tt}	h	0.805	0.800	1.919	1.408 - 2.925	1.857	1.453 - 3.053
Acc. Overlap time	T_{To}	h	0.423	0.545	0.925	0.490 - 1.315	0.896	0.517 - 1.607
Cycle time 1 path side	$CT_{sn}(1)$	s	82.2	68.7	612	569.0 - 722.0	610	572.0 - 709.4
Cycle time 1 path side	$CT_{sn}(2)$	s	5.5	5.1	140	134.9 - 146.3	140	134.8 - 144.9

Table 4.5 shows that the $\Delta y_{i,tot}$ ranges for MCA and DSA match well. On average 3.3 Monte Carlo simulations scored less than the minimum in the DSA range and 2.4 simulations scored above the maximum of the DSA range. Overall the outcome of DSA and MCA essentially agree and present no reason to dismiss DSA as a method for the GWorkS-model case. With stochastic models, an evaluation of DSA on total sensitivity using MCA should be done to conclude if DSA can be used for its main purpose, obtaining individual sensitivities.

4.7 Conclusion

4.7.1 Operational conclusions for harvesting operations in a static rose cultivation system

Sensitivity was determined at one operational point of the system, which was chosen from current practice in the Netherlands. It was considered as point of departure for labour efficiency improvement. The sensitivity analysis therefore represents a local method, applied at 5 yield levels and two harvest cycles. The model is essentially linear, meaning that relative sensitivity coefficients are valid for a larger parameter space than the evaluated system operation point. Validity boundaries were however not determined in this study. The GWorkS-rose model is not extremely sensitive for any of the 22 tested input parameters. The highest sensitivity in labour time is slightly above 1. Individual sensitivities change with crop yield. Specific findings are summarised in Sections 4.5.1 and 4.5.3. Parameters for which the labour time or throughput sensitivity is greater than 0.1, must be chosen with care. Within this group, eight parameters were identified, namely 2 greenhouse parameters $p_j \in P_g$, 4 operator parameters $p_j \in P_o$, 1 crop parameter $p_j \in P_c$, and 1 management parameter $p_j \in P_m$. These parameters are, section length ($L_{Gh} \in P_g$) and width ($n_{sp} \in P_g$), μ and σ in cutting performance ($(\mu(T_{cr}), \sigma(T_{cr})) \in P_o$), trolley speed ($v_o \in P_o$), and anticipation distance before cutting $D_o \in P_o$, yield ($Y_{n\ cf} \in P_c$), number of harvest cycles ($n_{hc} \in P_m$). Moderate sensitivity was found for average performance in rose net handling. The model is insensitive for standard deviations (in the natural logarithm) in service times for low frequent rose net handling actions. Under the condition that cycle time is not affected by resources like number of operators, throughput (stems s^{-1}) is the preferred indicator for labour efficiency as it accounts for yield effects.

Focal points of designers and growers for labour efficiency improvement are 1) technical aids or system modifications to improve rose cutting performance, 2) find ways to allow early and reliable anticipation for cutting a next rose, 3) evaluate whether a 2nd harvest cycle can be prevented, and 4) couple trolley speed with yield for Y_n<2 stems m^{-2}.

The main sources of model uncertainty are in parallel execution of actions and trolley speed. As a result, the coefficient of variation and the 99% uncertainty range is relatively large for accumulated transport time and overlap time. The uncertainty effect of these parameters in labour time, throughput and utilisation of the operator is acceptably small with CV < 5%.

4.7.2 Main conclusions of sensitivity analyses methods

Though reliability of single $S_{i,j}$ cannot be proven, a credible deduction is given that single $S_{i,j}$ are valid. For small perturbations of parameters which do not affect the total amount of roses harvested, the model can be considered linear and superposable at the chosen operation point of the system. That is, sensitivity coefficient $S_{i,j}$ for perturbation $\pm\Delta p_j$ is equal and perturbations in outputs are independent and additive. Sensitivity coefficients are valid over parameter ranges where linearity remains. Non-linear model response only shows for parameters with a direct yield effect. The internal constraints of DSA were thus satisfied for 1% parameter perturbation. Though system linearity and superposability was not proven for parameter perturbations above 1%, total sensitivity for DSA and MCA essentially agreed for perturbations as large as input uncertainties. Since results of MCA and DSA agree, it may be concluded that, for the GWorkS-rose model, DSA may in this case be regarded as a valid method for determining individual sensitivity. However, use of fixed random number series is required. The combination of both methods gives full insight into individual and total sensitivity of cumulative performance indicators for the GWorkS-rose model.

When simulations are used for design and scenario decisions, then at least total sensitivity must be determined to avoid the risk of invalid conclusions. Total sensitivity determined from DSA gives the validity interval of outputs for given (scenario defining) inputs. Total sensitivity determined from MCA gives the full probability density distribution of the output, which allows the probability of output being outside a given interval to be determined. Output ranges or confidence intervals of performance indicators outside each-others range, point out significantly different scenarios.

Overall, the model is a stable simulator of the harvest labour process in greenhouses. Sensitivity analysis points out the importance of parameters as well as output uncertainty. It thus provides data for well-founded conclusions based on simulation results.

4.8 Acknowledgements

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4.9 References

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Chapter 5

Integrated simulation of crop operations and model based work scenario selection in a static cut rose cultivation system

A. van ’t Ooster, J. Bontsema, E.J. van Henten, S. Hemming

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5 Integrated simulation of crop operations & model based work scenario selection in a static cut-rose cultivation system

5.1 Abstract

Worldwide competitive challenges urge Dutch growers to further improve operational performance. In this paper, the objective 'model based improvement of the operation of horticultural production systems' was narrowed to ranking simulated labour management scenarios in a cut-rose greenhouse. Eight scenarios with worker skill as a central theme were simulated including a practical labour management scenario applied by a Dutch cut-rose grower company. The crop operations harvest, disbudding and bending were considered, which represent over 90% of crop-bound labour time. The GWorkS-model was prepared for simulation of disbudding and bending in addition to harvest, as well as for full scale simulation of the greenhouse using all workers and equipment. The submodels on disbudding and bending were verified using data acquired in practice. Both processes were reproduced accurately. The model study on work scenarios showed that labour organisation choices might yield up to 5 s per harvested rose difference in total labour time for harvest, bending and disbudding between the best and worst scenario, which is equivalent to 7.1 € m^{-2} labour costs difference per year. Scenarios pointed out that working with low skilled, low paid workers is not effective. Specialised workers were most time effective, -17.5% compared to the reference, but overall a permanent team of skilled generalists ranked best in a multi-factorial assessment. Reduced crop operation diversity per day improved labour organisational outputs but ranked almost indifferent. The reference scenario was outranked by 5 scenarios. Overall, the GWorkS-model provided clear answers to research questions using the full complexity of crop operations.

Nomenclature

$c(C_s)$	Labour cost factor of skill class C_s (€ h^{-1})
C	Variable labour costs (€ $(1000\ roses)^{-1}$)
C_s	Skill class (-) ($C_s \in [1,5]$)
d_r	Decision parameter, for interpretation of worker roles ($d_r \in [1,2]$)
cf	gain or correction factor (-)
$E(\nu)$	Expectation of stochastic variable ν
$f(k,p(d))$	Execution frequency of crop operation k in 4 week period $p(d)$ ($days^{-1}$)
q_{BI}	biological gain factor representing intensity of axillary bud formation on flowering stems (empirical) (-)
GWorkS	Greenhouse Work Simulation, an acronym used as the model name
k	crop operation index number
L	Labour time per harvested rose (s)
n	node index number
N_{action}	Number of stems to bend at one location (-)
nD	Number of days of experience (d)
N_{TG}	number of stems to bend in a 5m section of a subnode *sn* in node *n* (-)
p	worker index number
$p_0,..,p_5$	Arbitrary probability for bending 0-5 stems in one bend location (-)
p_{bd}	Number of locations in a 5m subnode section where bend actions take place (-)
P_{bd}	Set of locations within a 5m subnode section where p_{bd} is sampled from (-)
P_p	Personal potential in task performance (-)
r	Correlation coefficient
RRMSE	Relative root mean squared error
SD	Standard deviation
T_{db}	Stochastic variable service time of a disbud action (s)
T_{bn}	Stochastic variable service time to bend n stems at one location (s) ($n \in [1,5]$)
$T_{T,d}\ (n,k)$	Total labour time during day d within task k in node n (s)
$T_{T,d}\ (p,k)$	Total labour time of worker p during day d within task k (s)
T_{TG}	Active time bending in a 5m section of a subnode *sn* in node *n* (s)
wf	weight factor of model outputs in scenario ranking
$V(\nu)$	Expected variance of stochastic variable ν
$Y_n(d)$	Measured daily yield in node n on date d (stems m^{-2})
$Y_{n,d}$	Yield in node n at day d in units of product
μ	mean of the variable's natural logarithm for pdf-type $LN(\mu,\sigma^2)$ or the variable itself for pdf-type $N(\mu,\sigma^2)$
σ	standard deviation of the variable's natural logarithm for $LN(\mu,\sigma^2)$ or the variable itself for $N(\mu,\sigma^2)$

5.2 Introduction

Dutch growers face numerous competitive challenges. One challenge is that greenhouse crop production requires extensive manual labour, while at the same time the wage level is high, competition from low wage countries increases, and lack of human resources is a persistent problem. Crop operations in greenhouses are essentially men operated because of a vulnerable, highly variable and complex work environment (Bechar & Edan, 2003), (Ota et al., 2007). In the near future, crop operations in modern greenhouses require strong innovations to minimize production costs. Growers have to innovate labour consuming processes using operations management and upcoming technology, but they don't know how. A competitive production system should show high operational performance through effective control of crop operations, accurate and timely execution of tasks, as well as effective use of workers and technology. Rose growers yearly produce millions of flowers per hectare and tend to increase scale. Small efficiency improvements per flower may yield substantial savings in labour time, cost, and resources. This raises questions like how to execute crop operations effectively, how to use (new) resources and what innovations really add value to the system. In industry, work methods analysis, lean manufacturing and simulation are commonly used techniques to improve production, operations management and labour efficiency (Hopp and Spearman (2008), Shah and Ward (2003)). We have adopted a similar approach to improve operations management and labour efficiency in greenhouses. The focus of this paper was model based improvement of the operation of horticultural production systems.

Crop operations and labour/operations management strategies in cut-rose production were used as a case study. The Greenhouse Work Simulation model, GWorkS, was initially developed for harvest of roses (van 't Ooster, Bontsema, van Henten, Hemming, 2012, 2013, 2014). For this study, GWorkS was extended for integrated simulation of labour in multiple, substantially simultaneous crop operations in a Dutch cut-rose greenhouse. By integrating crop operations in one simulation the full complexity of operations management in horticultural practice is represented. Operations management includes selection and allocation of workers and production means, operation scheduling, efficient task execution, and minimum backlog of operations (Mönch, Lendermann, McGinnis, Schirrmann, 2011).

Human operated crop operations in the production stage of cut-rose are: harvest of ripe flowers, prune axillary buds (disbudding), bend unproductive stems (bending), break superfluous buds, cut imperfect non-saleable flowers, prune redundant stems, protect plants, and maintain substrate. Harvesting, disbudding, bending and other crop operations represent some 60%, 18%, 15%, and 7% of total labour time in the nursery, respectively. For this reason, crop operations other than harvest, disbudding and bending were not considered in this study.

The process of harvesting is described in (van 't Ooster et al., 2014). Disbudding is the process of removing sprouted axillary buds from the top half of harvestable flowering shoots in order to improve growth of stems and flower quality (Marcelis - van Acker, 1994; Getachew, Kassa, Mohammed, 2012). Bending is the singular or repeated application of force to the base of a shoot resulting in horizontal growth of the shoot (Buck-Sorlin et al., 2011). Bending of non-productive stems and poor quality stems contributes to better accessibility of the vertical flowering shoots and maintains assimilate source capacity (Kool & Lenssen, 1997), thus increasing production rate and flower quality (Lieth & Kim, 2000; Getachew et al., 2012). The crop operations disbudding and bending were added to GWorkS and verified.

Finding the best scenario is an essential part of the model-based method for analysis and assessment of alternative business operations. Scenarios were defined based on research questions. In this paper the research questions were formulated and motivated from the growers viewpoint and his applied operations management and labour organisation. The practically relevant and model challenging research questions were: Q1: Is it profitable to work with low skilled, low paid employees?, Q2: What is more effective, to work with generalists or specialists?, Q3: Is it smart to reduce the number of crop operations per day?, Q4: Does management affect the labour costs and profile of daily labour requirement? To answer the questions, eight alternative scenarios for operations management in a cut-rose greenhouse were simulated. As a reference, the scenarios included a practical labour management scenario as applied in a Dutch cut-rose grower company. In the scenarios, worker and equipment selection and allocation in crop operations was a central theme.

The paper is organized as follows. Section 5.3 describes new components of the GWorkS-model. Section 5.3.1 presents IDEF3 process models for disbudding and bending. The GWorkS-model status is described in Sections 5.4 and 5.4.1. Specifics on modelling of the crop operations disbudding and bending is given in Section 5.4.2. Implementation of operational resources in GWorkS is described in Section 5.4.3. Materials and methods on data and model verification are given in Section 5.5. Scenarios are described in Section 5.6. Section 5.7 presents and discusses verification results on submodels and scenario simulation results.

5.3 GWorkS-model

5.3.1 IDEF3 process models of three main cut-rose crop operations

The process flow of the crop operations in a cut-rose production system was captured using the Integrated Definition method for process description capture, IDEF3 (Mayer et al., 1995; Jeong, Cho, Phillips, 2008). Fig. 5.1 positions the main crop operations, harvest, bending, and disbudding in the manager controlled task execution of workers. Harvest has the highest priority and time allocation. Normally, each day the first shift is devoted to harvesting. Most workers will start other crop maintenance tasks after completing the assigned harvest task. At system level, harvest, disbudding and bending are not synchronously executed but may overlap in time. The daily labour capacity within each task depends on availability and allocation of workers and equipment.

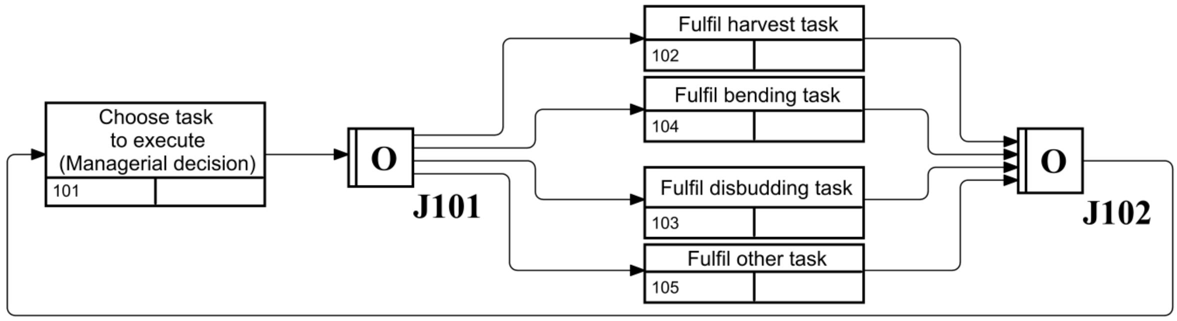

Fig. 5.1 - Process flow diagram of main crop operations in a static cut rose production system for individual workers

Harvest, bending and disbudding were detailed in IDEF3 prior to implementation in the GWorkS-model as sub-models. The process flow diagram for harvest was presented in van 't Ooster et al. (2014). The process flow diagrams of the disbudding and bending operations are displayed in Fig. 2 and 3 respectively.

In the disbudding operation (Fig. 5.2), the workers use an electric trolley to move faster and to have better access to the upper part of the stems. Workers do not use any cutting or buffering equipment.

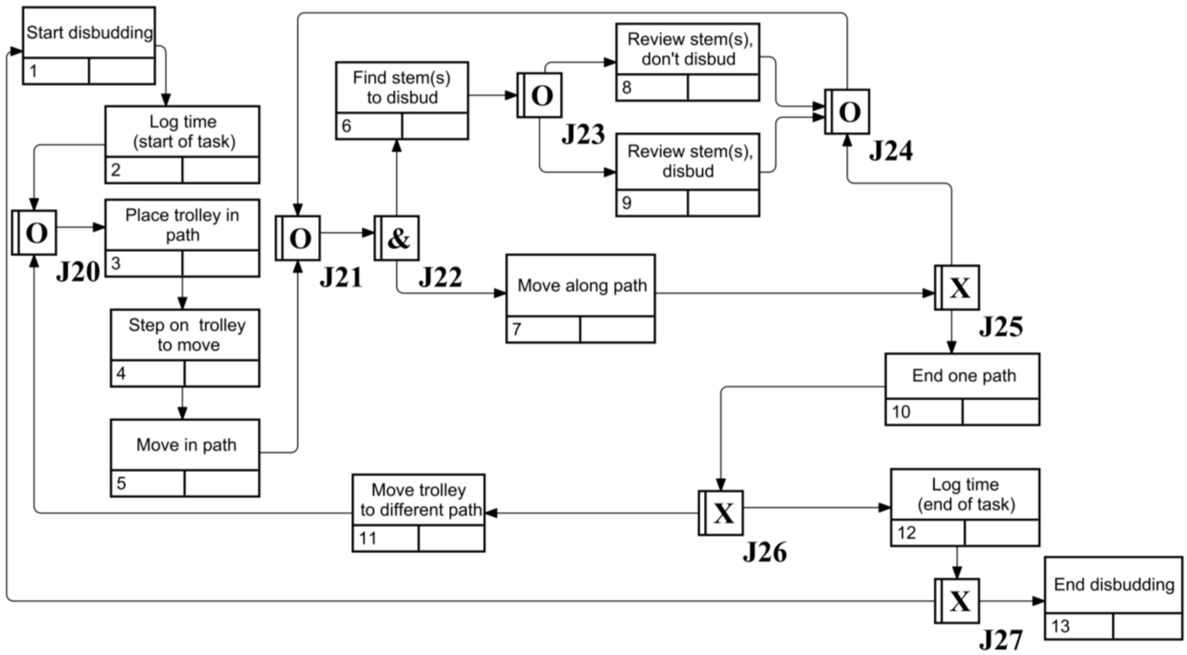

Fig. 5.2 - Process flow diagram of a worker task within the crop operation disbudding

At the start of the disbudding operation, the workers ‘log time’ (2). The asynchronous OR (J20) indicates they either start a new path or start the task. Time logging is restricted to the start and end of a shift. Time logging of single paths is not included in the cycle of events. The actions ‘find stems to disbud’ (6) and ‘move along path’ (7) are parallel actions linked with an asynchronous AND junction (J22). The actions (6) and (7) follow after initiating a path or after a stop within a path (J21). Asynchronous OR junctions (J23 and J24) branch ‘review stem(s), don’t disbud’ (8) and ‘review stem(s), disbud’ (9) as either one of these actions is executed. After completing one disbud action the worker ‘moves along the path’ and ‘finds another stem to disbud’ or leaves the path when it is finished, as the exclusive OR junction (J25) expresses. After ‘end one path’ (10), the worker ‘moves trolley to different path’ (11) or ‘logs time’ (12) to mark the (intermediate) end of the disbudding task (J26). After finishing the assigned paths, the worker ‘ends disbudding’ (13) or proceeds the assigned disbud task after an intermediate end (J27).

The process flow diagram for the bending operation is shown in Fig. 5.3. During bending, the workers walk along the path without equipment, as the work takes place at the base of the rose plant and a trolley does not allow ergonomic work postures. The process flow is similar to disbudding. However, in bending, workers stop to grab the stems with both hands, one hand in low and one hand in high position, and either bend the stem into the path or into the rose bed.

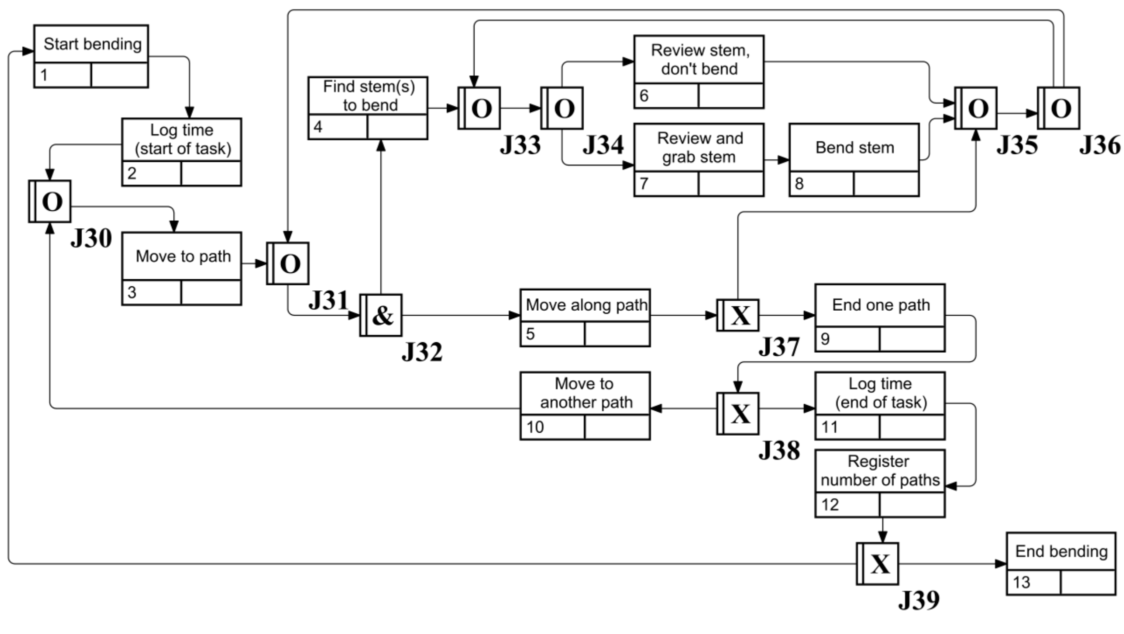

Fig. 5.3 - Process flow diagram of a worker task within the crop operation bending

The worker ‘logs time’ (2) before starting the process, but not between paths (J30). ‘Find stem(s)’ (4) and ‘move along path’ (5) are parallel actions branching from an asynchronous AND (J32). ‘Review stem, don’t bend’ (6), ‘review and grab stem’ (7) and ‘bend stem’ (8) were linked by asynchronous ORs (J33-J36) as either one of the action lines is executed. If more stems to bend are found in one location the sequence between junctions J33 and J36 repeats until all stems in that location are bent. The worker completes one path (9) or continues to move along the same path (5). After completing a path, the worker starts bending in a new path (J38) or 'logs time' (11) and 'registers the number of paths completed' (12) to end the task or to restart it after an intermediate end (J39).

5.4 Current status of the GWorkS-model

The main structure of the GWorkS-model is shown in Fig. 5.4. Details on previous model versions are given in (van 't Ooster et al., 2012, 2013, 2014). In the current study, the GWorkS-model was extended from simulation of the harvest operation by up to 3 workers active in one greenhouse section, to substantially simultaneous crop operations executed by multiple workers active in multiple greenhouse sections.

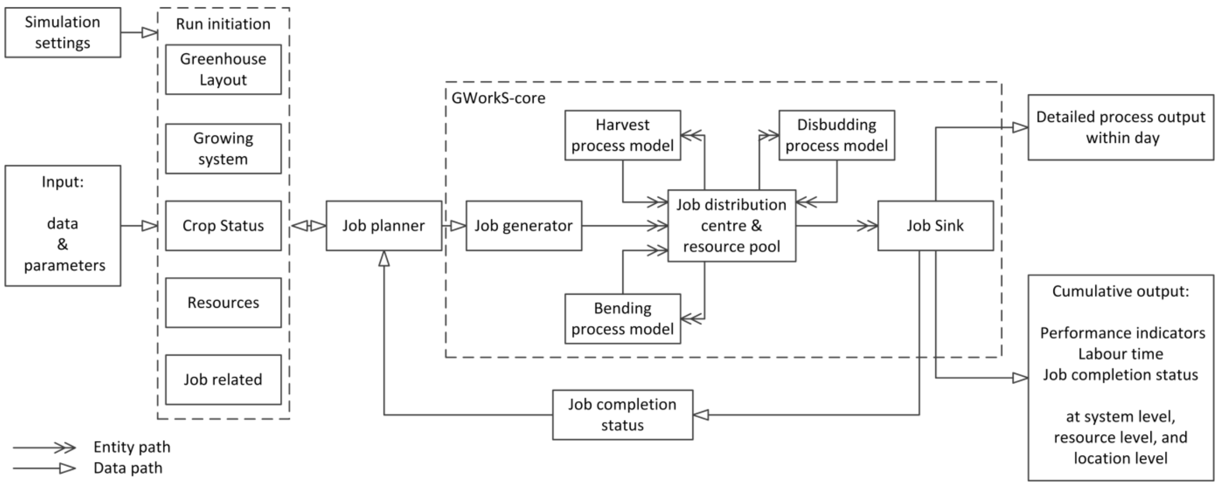

Fig. 5.4 - Main structure of the GWorkS-model with position of the process models disbudding and bending indicated

The blocks 'Simulation settings', 'Input', and 'Run initiation' prepare the simulation of a series of workdays in a spatially defined greenhouse and crop system with predefined coordinates of locations of action for each operation. In 'Simulation settings' the user chooses the simulation period, how to use resources, and what greenhouse sections are simulated, as well as output options. The most relevant resources in GWorkS are employees, trolleys, rose buffers and accessories for task performance. The 'Input' block provides the model with data on crop yield, crop operation frequencies, on the worker/machine population and on worker/machine availability. The smallest area for which input data are available is a greenhouse section. In the model, and in line with terminology of discrete event systems, a greenhouse section is called a 'node'. The 'Run initiation' is updated daily to provide the job-planner with current data on crop operational status 'Crop status', available 'Resources', and 'Job related' constraints. Details on worker resources are given in Section 5.4.3. The two output blocks on the right of Fig. 5.4 process simulation results. The block 'detailed process output within day' contains timed signals of the day with information such as per worker realised action times for each rose harvested, for each disbud action and each bend action, and per worker realised processing times per path side. The block 'cumulative output' reports process performance indicators, labour time, labour time composition and the job completion status of the day. The smallest areal unit considered in the cumulative model output is one side of a path. This is referred to as a 'subnode'. Job completion status is a feedback to the 'Job planner'.

The 'GWorkS-core' represents the discrete event system where crop operations are simulated in process models. The 'Job planner' defines all crop operational tasks in a task list. In the GWorkS-core, the 'Job generator' decomposes the task list into location specific lists and generates job-entities to flow through the GWorkS-core network. Each job-entity carries the task list for one greenhouse section as an attribute. Inside the 'Job distribution centre & resource pool', job routing is handled. This means one element in the task list is activated as the current task in case of sequential execution of crop operations, or more elements are activated in one or more crop operations by splitting the job-entity into smaller job-entities in case of simultaneous task execution. Also inside the 'Job distribution centre & resource pool', job-entities allocate resources. The resource pool manages the status of workers, trolleys, rose buffers, and accessories like nets for binding roses. The resource pool designates resources until it depletes. When a required resource is depleted, the job-entity is delayed. The flow of job-entities to process models is thus constrained by the availability of both human and material resources with (individual) properties. The current task of a job-entity is executed or queued upon arrival at a process model. A job-entity remains in the GWorkS-core until all tasks in the task list are executed or when an end-of-workday occurs. After completing report and feedback functions the job-entity is destroyed in the 'Job Sink'.

5.4.1 Process models

Each process model in the GWorkS-core simulates a different crop operation. The calculation resolution is a single action as defined in the IDEF3 process flow diagrams in Section 5.3.1. A process model is a multi-operator model, in which many composite entities are simultaneously active. In a process model, job-entities migrate into composite entities that represent combinations of worker, equipment and accessories. Each composite entity executes a single crop operation process in all path sides (subnodes) assigned to one worker within one greenhouse section (node). For this, in the 'Disbudding process model' a composite entity temporarily expands to a worker (resource), with trolley (resource), accessories (resource), and a specific path side (subnode) containing all data required to perform the disbud operation in given subnode. The number of job-entities allowed to a process model is constrained by a user defined number of Kanban-entities as used in 'Lean manufacturing' (van 't Ooster et al., 2012). A Kanban-entity authorises a job-entity to be executed. The task execution is simulated down to the level of the location of an action at given coordinates. For instance a 'bend action' is executed if the coordinates of the worker and the 'stem to bend' are within a predefined distance. Probability density functions generate the service time per action. Task completion status is registered at subnode level. During user defined workdays, a process model is open for task execution in an user defined limited time span. At the end of a workday a worker finishes the subnode in progress and abandons the task.

All process models interact in time and space, as crop operations are executed in order of priority and task progress depends on resource availability. The GWorkS-core prevents space contradiction when simultaneous execution of two tasks in one subnode or path is not allowed. Because of interaction, simulation of separate processes for non-critical operations such as bending and disbudding is not realistic. It is therefore necessary to simulate harvest also.

5.4.2 Process models disbudding and bending

Specific inputs of the disbud model are daily yield per greenhouse section Y_n, the intensity of axillary bud formation g_{BI}, path visit frequency $f(2, p(d))$, and parameters μ and σ defining the lognormal probability density function for a single disbud action. The disbud process operates on harvestable flowering shoots. All roses harvested within the time interval between two disbud cycles are assumed to be disbudded prior to harvest. In practice, a worker decides to disbud a stem based on the development stage of the flower. The number of axillary bud breaks on each stem is affected by temperature and assimilate supply (Marcelis - van Acker, 1994). Dutch cut rose greenhouses show extensive supplementary lighting during many hours a day in winter and shading during the summer. This results in effective assimilate supply and more axillary bud breaks per stem in winter. To account for this, the model input g_{BI} ranging from 1 in midsummer to 3 in winter was defined as the ratio between the expected number of disbud actions and the number of roses harvested in the time interval between two disbud cycles. Expected g_{BI} , $E(g_{BI})$, was estimated from personal communication with the rose-grower and from registered data.

Specific inputs of the bending model are the daily expected number of stems to bend per path section $E(N_{TG})$, the probabilities p_0-p_5 to bend 0-5 stems in one stop, the task execution frequency $f(3, p(d))$, and parameters μ and σ defining the lognormal probability density functions for bending 0-5 stems. Workers stop for each bend action to bend 0-5 stems. The number of bends is not evenly distributed along a path. Therefore, the model input $E(N_{TG})$ was estimated from a regression equation T_{TG}=a N_{TG} + b, using the average measured work time per path section T_{TG} and regression coefficients a, b. In the model, the number of stems to bend was randomly assigned to path side sections of 5m, based on a lognormal distribution, with parameters μ and σ determined from the expected number of stems to bend per path section $E(N_{TG})$ and observed SD. The lognormal distribution was cut off at the equivalent of 1.5 stems bent per plant. The number of stems to bend in a stop was sampled from an arbitrary discrete probability distribution function with probabilities p_0-p_5 for 0-5 stems to bend. The sampled number of stems to bend was randomly assigned to an action location using sampling without replacement from P_{bd} predefined locations until the total stems to bend equalled N_{TG}. This resulted in p_{bd} action locations within a path section.

5.4.3 Individualised workers

In GWorkS, a limited number of resources with individual properties was used since neglecting capacity limits in decision-analytic models with evident scarce resources may cause wrong cost-effectiveness results (Jahn, Pfeiffer, Theurl, Tarride, Goeree, 2010). Therefore, individual resource properties were defined as entity attributes, which is illustrated for workers.

With respect to performance of individual workers the concept of learning curves was used. Schilling, Vidal, Ployhart, Marangoni (2003) present several learning curves used in management science. Learning curves express the direct labour time to produce the *x*th unit which decreases with *x*. In GWorkS the following model assumptions were used, 1) Workers have a randomly defined personal potential P_p sampled from a normal distribution with mean equal 1, and SD equal 0.1288, P_p=N(1, 0.1288), 2) Skill progression in time is defined as a performance gain cf_{Exp} which is equal for all workers and based on days of experience *nD* in each crop operation with value 1 for experienced workers and less than 1 for workers in learning, 3) Each active day in a crop operation adds to the number of experience days *nD* = *nD* + 1, passive days decrease experience 1% per week, 4) P_p was derived from registered harvest rates and is assumed to be equal for all crop operations. If P_p =1 and cf_{Exp}=1 the worker performance in units per hour is equal to company average performance. The parameter *nD* categorized workers in skill classes C_s with values 1 (not skilled) to 5 (very skilled). Workers start in an initial skill class $C_s(t_0)$ which migrates with *nD* according to Table 5.3 in Section 5.5. The performance gain was derived from grower data,
$cf_{Exp} = 5 \cdot 10^{-3} {C_s}^3 \; - \; 8.21 \cdot 10^{-2} {C_s}^2 \; + \; 4.63 \cdot 10^{-1} C_s \; + \; 1.14 \cdot 10^{-1}$.

Individual parameters μ and σ of action defining probability density functions were obtained based on personal potential P_p and performance gain $cf_{Exp}(C_s)$. Two gain factors cf_E and cf_V convert measured expected mean $E(\nu)_m$ to individual expected mean $E_{ind}(\nu) = cf_E \cdot E(\nu)_m$ and measured expected variance $V(\nu)_m$ to individual expected variance $V_{ind}(\nu) = cf_V \cdot V(\nu)_m$. The gain factors were defined as: $cf_E = \left(P_P \cdot cf_{Exp}\right)^{-1}$ and
$cf_V = \begin{cases} 1 + 0.25(cf_E - 1), \; if \; cf_E > 1 \\ 1 + 0.43(cf_E - 1), \; if \; cf_E \leq 1 \end{cases}$. The factor cf_E represents the individual learning curve. The probability density functions of the disbud action of the least skilled worker 19 and the most skilled worker 118 are given in Fig. 5.5 as an example.

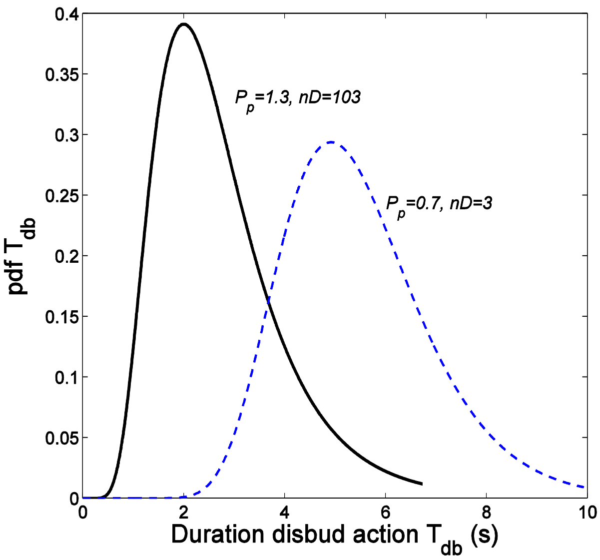

Fig. 5.5 - Probability density functions of the least and most skilled worker performing a disbud action T_{db}. The least skilled worker 19 has personal potential P_P=0.7 and no work experience nD=3 (dashed line), the skilled worker 118 has P_P=1.3 and nD=103 (solid line).

For model flexibility in using resource constraints, resource and worker mode were introduced (Table 5.1). The main options were 1) limited or unlimited resource availability, and 2) individual or average properties for workers. In 'Individual Workers' mode, the model uses individual parameters for workers with an active role in a crop operation. Workers with highest skill class C_s in a crop operation are selected first. In 'Average worker' mode all workers were given static equal parameter values with exception of role. Depending on role interpretation by the model, having no active role in a crop operation results in pupil skills or in exclusion from that operation. Model input on operational resources was extracted from the labour registration data for the reference scenario and set manually for other scenarios.

Table 5.1 - GWorkS run mode settings for using resources in simulations.

Resource mode	Worker mode	Description
Unlimited	Average worker	Per resource type one generic entity which is replicated on demand, parameter values are static
Unlimited	Individual workers	Oversized population of entities per resource type, individual parameter values for workers, group values for equipment
Limited	Average worker	Limited number of entities per resource type, parameter values are static
Limited	Individual workers	Limited number of entities per resource type, individual parameter values for workers, group values for equipment

5.5 Grower data

This Section describes data acquisition for model input and data acquisition for independent datasets to calibrate and verify the submodels of the operations disbudding and bending. Data originate from a 3.6 ha cut-rose producing greenhouse with static growing system at

Van den Berg Roses, Delfgauw, The Netherlands, which is described in detail in van 't Ooster et al. (2014). Data were acquired using the Dytime® labour registration system of the grower and Sony DCR-SR78E cameras. Data processing and analysis was conducted using MS-Access, MS-Excel, Matlab® and the behavioural research software Noldus Observer XT®. Time distributed model inputs originated from the labour registration data. Video recordings registered worker activity and location of action. The recordings supported modelling in IDEF3 and SimEvents® and provided raw data for time invariant model input parameters of probability density functions of basic human actions.

From June 2011 till December 2012, the cut-rose yield per greenhouse section and the timeline per individual worker were acquired daily. The timeline indicates the worker status as a function of time. Worker status numerically represents the crop operation in progress. With respect to disbudding and bending, the labour registration system did not register the paths processed nor the number of actions within paths. For bending, the grower registered the number of paths processed from May 2012, but path number and location remained unknown. Path visit frequency for harvest was acquired directly from registered data. Because of data limitations, path visit frequency for disbudding and bending were obtained from personal communication with the grower.

The probability density functions of basic actions for disbudding and bending were obtained from analysis of video recordings in 5 and 4 paths respectively in a total of 240 paths. The analysed video was recorded on June 9th 2011 for disbudding, and on June 29th and July 2nd 2012 for bending. In Table 5.2, the resulting parameters of the probability density functions of basic actions are listed as well as the arbitrary discrete probabilities p_0-p_5 for occurrence of 0-5 bend actions per bend action.

Based on a 5m path section, video data also produced the average number of stems bent per path section N_{TG} and the SD between path sections. Measured N_{TG} ranged 4.3-10.3 and N_{TG} and SD were linearly related, SD=0.2948 N_{TG}+ 0.562. The gross labour time per path section best fitted the regression equation T_{TG}=a N_{TG} + b, with a=5.28 ($\pm$0.47) and b=9.42 ($\pm$ 7.8) , r^2=0.63. In brackets, the 95% confidence interval is given. Even though the regression coefficients are of low quality and general validity for rose cultivars is uncertain, the coefficients a, b were used to estimate model input N_{TG}.

Table 5.2 - Probability density functions (pdf) for the sub-models disbudding and bending obtained from video data collected at Van den Berg Roses. A single disbud action and bend actions with *nb*=0-5 stems bent per worker-stop with the probability p_n given in brackets. The μ and σ are the mean and standard deviation of the variable's natural logarithm (lognormal), with the confidence interval (α=0.05) given in brackets, n is number of observations. For T_{b5} (p_5=0.0011) with n=1, a normal distribution with SD= 0.1 was assumed.

Inputs		Symbol	Pdf type	μ	σ	n
Disbud action service time		T_{db}	Lognormal	0.90 [0.89-0.92]	0.46 [0.44 -0.47]	3304
Bend action service time with *nb* stems to bend per stop (probability)		T_{bn}				
nb=0	(p_0=0.3257)	T_{b0}	Lognormal	0.812 [0.75-0.88]	0.553 [0.51-0.60]	296
nb=1	(p_1=0.4934)	T_{b1}	Lognormal	1.416 [1.37-1.47]	0.548 [0.51-0.59]	450
nb=2	(p_2=0.1502)	T_{b2}	Lognormal	1.962 [1.88-2.05]	0.503 [0.45-0.57]	137
nb=3	(p_3=0.0197)	T_{b3}	Lognormal	2.389 [2.21-2.57]	0.369 [0.28-0.55]	18
nb=4	(p_4=0.0099)	T_{b4}	Lognormal	2.826 [2.53-3.12]	0.379 [0.26-0.73]	9
nb=5	(p_5=0.0011)	T_{b5}	Normal	14.68	0.1	1

For calibration and verification, three independent datasets were extracted from the raw data. Dataset 1 was used to test and calibrate the submodels disbudding and bending. It contained data of the fully analysed video recordings (June 9th 2011, June 29th and July 2nd 2012). Dataset 2 was used to verify the disbudding model. It contained labour registration data on disbudding of two periods. Period one is in winter with high g_{Bl}, from week 48, 2011 till week 4, in 2012, November 28th 2011 till January 29th 2012 and period two in summer with low g_{Bl}, week 27-35, July 2nd till September 9th 2012. Dataset 3 was used to verify the bending model. It consisted of data on bending for one period in summer 2012, weeks 27-39, July 2nd till September 30th.

The submodels disbudding and bending were calibrated for workload inputs, transport velocity and the workers ability to synchronously move along the path and execute a basic action as defined in Table 5.2. The calibration aimed for a simulation accuracy close to one for the model outputs: labour time, action time, transport time, overlap time of transport and the bend or disbud action itself, and number of stems processed. Simulation accuracy was defined as the ratio (S/M) of the simulated mean of 10 simulations (S) and the measured result (M).

The calibrated models were used for verification of the submodels disbudding and bending for longer periods, dataset 2 for disbudding and dataset 3 for bending. Simulations were carried out for the whole greenhouse, since data did not specify labour time for greenhouse sections. This prohibited comparison in time and space at section or path level. The daily number of active workers in the greenhouse was equal in simulation and in practice, but the workload assigned to each worker was determined by the job-planner.

For verification of the disbudding model weekly totals were compared as the greenhouse was disbudded weekly. This avoided effects of daily differences between measured and simulated results. Conform practice, in period one of dataset 2, 6 weekdays (Sundays excluded), and in period two, 4 weekdays (Mon, Tue, Thu, Fri) were used for disbudding.

For verification of the bending model not only weekly totals, but also measured and simulated cycle time per path were compared since in practice, task execution was irregular. One period was selected because for bending no typical seasonal pattern exists and in the given period start-up problems on registration of the number of paths processed were alleviated.

To be able to analyse the effect of different properties amongst individual workers, each worker in the database was given an identification number and for each worker, roles, experience, and performance rates were extracted from the labour registration database and processed in Visual Basic. A population of 180 workers resulted, of which 109 were involved in harvesting, 150 in disbudding and 102 in bending. Daily, for each crop operation, the participating workers were identified. Table 5.3 presents the skill class C_s distribution of all workers observed. This skill class resulted from counting individual experience days for each crop operation in the main dataset. Also for equipment, separate resource units were defined as model input. The greenhouse was equipped with 26 electrical trolleys and 30 water filled buffers to collect product in the main aisle.

Table 5.3 - Skill class definitions based on measured number of active days in a crop operation. The initial class-distribution is given for workers at Van den Berg Roses. *nD*= measured experience (days), h= harvest, db=disbudding, bd=bending.

Skill Class C_s	Experience days per Class nD	Initial state in experience class		
Crop operations		h	db	bd
1 - not skilled	$nD \leq 21$	29	82	36
2	$21 < nD \leq 42$	11	13	19
3	$42 < nD \leq 63$	7	4	16
4	$63 < nD \leq 94$	16	9	10
5 - very skilled	$95 < nD$	46	42	21
Total		109	150	102

5.6 Scenario simulation

To improve labour efficiency and workflows, different labour management scenarios dealing with all crop operations of interest were simulated. To assess crop operations in the mid-long term, simulations were conducted for a 9 weeks period, Monday July 2nd till Sunday

September 2nd, 2012. Investigated parameters in the scenario study were, number of available workers and units of equipment, prioritisation for skill, skill level of workers, specialised versus non-specialised workers, prioritisation of operations.

A scenario based on labour registration data of a 3.6 ha greenhouse at Van den Berg Roses was used as a reference scenario S0. In S0, the daily number of operational human and material resources as well as roles in crop operations and crop operation specific workdays of the week were equal to practice. During the simulation period, the measured daily number of operational workers in 20 greenhouse sections ranged from 29-45 people, with mean 37, SD 3.6. During workdays, the number of workers harvesting ranged from 22-36, with mean 25.9, SD 2.6, disbudding from 9-32 workers, with mean 20, SD 5.9, and bending ranged from 2-25 workers, with mean 16.9, SD 5.3. A full match with practice was not pursued for task assignments to individual workers, for worker properties, and for selection of workers based on experience skill as these elements followed the model algorithm.

5.6.1 Scenarios

In addition to the reference scenario S0, alternative scenarios S1-S7 were simulated to address the research questions Q1 to Q4 stated in Section 5.2. All scenarios are summarized in Table 5.4.

Table 5.4 - Summary of simulated scenarios.

Code	Scenario name	Description
S0	Practice (reference)	Mimics practice at the 3.6 ha greenhouse at Van den Berg Roses, 20 sections
S1	Low skilled workers	High replacement rate of workers, low average skill
S2	Generalists	Permanent highly skilled staff active in all crop operations
S3	Specialists	Specialised highly skilled workers active in one crop operation only
S4	Non-prioritised generalists	Standard skilled, non-specialised workers and non-prioritised worker selection
S5	Two crop operations	The crop operations bending and disbudding were separated in time
S6	Single tasks	Instead of ordered structured job-entities with tasks aligned to priority, single task job-entities were generated. Job execution was on a first in, first out basis
S7	Average workers	Unlimited resources with equal properties for all workers

To answer Q1: Is it profitable to work with low skilled, low paid employees?, Scenario S1 was simulated. In S1, a high replacement rate of workers with low skill was chosen. When skill class 3 was reached, a worker was replaced by a pupil with skill class one and matching individual properties.

To address Q2: What is more effective, to work with generalists or specialists?, the Scenarios S2, S3 and S4 were used. In S2, the available number of workers was reduced to a small group of 35 permanent highly skilled generalists, all in skill class 5. The number of workers was slightly under the practical mean of 37. In S3, the effect of a limited number of specialised highly skilled workers active in one crop operation only was targeted with 26, 20 and 17 workers active in harvesting, disbudding, and bending respectively. The number of workers was equal to the measured mean of the crop operation. Individual worker roles and skills for people specialised in one job were used. Personal potential P_p mean was 1.25, SD 0.116, a 10% higher average for transport velocity and 20% better anticipation for actions. In S4, the effect of standard skilled, non-specialised workers with standard personal potential P_p (Section 5.4.3) and non-prioritised worker selection was simulated. Each worker performed all roles, the number of resources was unlimited and parameters were individualized to obtain distributed skill within the group.

In answer to Q3: Is it smart to reduce the number of crop operations per day?, Scenario S5 was used. In S5, execution of bending and disbudding was separated in time. Disbudding was planned on Mon, Tue, Wed. Bending was planned on Thu, Fri, Sat. Unfinished work was completed on Sundays.

To address Q4: Does management affect the labour costs and profile of daily labour requirement?, the results of Scenarios S1-S5 and the newly added Scenarios S6 and S7 were compared. In Scenario S6 the priority settings for execution of crop operations was abandoned. Instead of ordered structured job-entities with tasks aligned to priority, single task job-entities were sent into the GWorkS-core at the start of the day. Job execution was based on first in, first out and proceeds until resources deplete. Remaining jobs were executed when required resources became available until all jobs were completed or the end of the workday was reached. In Scenario S7, unlimited resources were available, worker properties were average, and workers once started were given a high priority to keep them in the system in successive task assignments. S7 represented a situation without resource limitation and with denial of differences between workers.

Skill settings in Scenarios S5 and S6 were equal to the settings of S0 (Table 5.3), with standard personal potential.

5.6.2 Scenario assessment

A multi-factorial assessment of the scenarios was performed based on daily performance indicators. These indicators were labour time *L* and labour costs *C*, number of workers used, utilisation of workers, tardiness of task execution, and percentage of roses not harvested. The time series of 63 days was assessed with one day (*d*) as unit of time and for all indicators totals, mean, SD, and min and max values were determined both per crop operation and for all operations.

Labour time was available as daily totals $T_{T,d}(n,k)$ per node *n* and crop operation *k* and as daily totals $T_{T,d}(p,k)$ per worker *p* and crop operation *k*. Labour time *L* per harvested rose

(s) was determined as the ratio of the sum of labour time $T_{T,d}(n,k)$ for all days, nodes, and crop operations and the sum of harvested product $Y_{n,d}$ for all days and nodes. Consequently, labour time for disbudding and bending was allocated to harvested roses. Variable labour costs C in euros per 1000 stems, was determined from the ratio of the sum of labour costs $T_{T,d}(p,k)c(C_s)$ for all days, workers and crop operations and the sum of harvested product $Y_{n,d}$ for all days and nodes in thousands. $c(C_s)$ is the labour cost factor in euros per hour for a worker in skill class C_s. Assumed labour cost factors were 10, 12, 14, 16, 16 euros per hour for the 5 classes respectively, in line with current collective labour agreements.

Timely completion of periodic tasks was determined from tardiness assessment. Normally, daily available time for non-harvest operations, depends on resource availability and time allocation for harvest. Tardiness was defined from the sum of the daily number of subnodes in crop operation *k* not processed in time.

Utilisation equal 1 means that the operational resource is used for a full workday, 0 means it is not used. Lower utilisation of workers points to ineffective use and economic damage depending on the waging system used. To expose ineffective use one minus mean worker utilisation and SD of the mean worker utilisation were the parameters used in scenario assessment.

To rank the scenarios, normalised results were used. The range of each performance indicator of eight scenarios, S0-S7, was split into 5 equidistant intervals. Scenarios were scored 1-5 for best to worst based on the interval in which the indicator is situated. The single indicators were ranked. The overall ranking of a scenario resulted from the sum-product of the single indicator ranks and a weight factors *wf.* Since effects of utilisation, mean number of active workers and SD of mean utilisation and number of workers are not well known, they were given a weight factor 0.5 instead of 1.

5.7 Results and discussion

Section 5.7.1 describes the results of the calibration and verification of the submodels for disbudding and bending, Section 5.7.2 presents the scenario simulation results and in Section 5.7.3 these results are discussed.

5.7.1 Calibration and verification of submodels disbudding and bending

The calibration results are given in Table 5.5. The accuracy, defined as the ratio between simulated mean and measured result, was close to 100% for both labour time and cycle time per subnode. Also for the labour time details, action time, transport time and overlap time, accuracy is within 10%. For disbudding the accuracy of standard deviation SD between subnodes was not accurate.

Table 5.5 - Calibration of disbudding and bending submodels based on video recordings. For disbudding and bending, 10 simulations on 5 and 4 paths were executed. The average and SD were compared to the results of video analysis.

Performance in process	Disbudding (10 subnodes, 5 paths)				Bending (8 subnodes, 4 paths)			
	Measurement (M)	Simulation (10)		Accuracy	Measurement (M)	Simulation (10)		Accuracy
		Mean (S)	SD	ratio S/M		Mean (S)	SD	ratio S/M
Stems (-)	3314	3299	99.0	100%	889	896	31.5	101%
Labour time (h)	2.73	2.72	0.03	100%	1.54	1.49	0.03	97%
Action time (h)	2.51	2.53	0.03	101%	1.34	1.28	0.04	95%
Transport time (h)	0.67	0.68	0.00	101%	0.38	0.36	0.01	94%
Overlap move - action (h)	0.53	0.49	0.01	92%	0.15	0.14	0.00	97%
Cycle time subnode (min)	16.4	16.5	0.18	101%	11.5	11.4	0.62	99%
SD subnodes (min)	2.2	4.8	0.91	218%	-	1.12	0.27	

The accuracy of the bending model for labour time was 97% and for subnode cycle time 99%. Also for labour time details accuracy was greater than or equal to 95%. The standard deviation between subnodes was not measured.

For verification of the process model disbudding, simulations were carried out during two periods of 9 weeks. Fig. 5.6 shows the simulation results projected in the pattern of measured results. Deviations in weekly totals range from +8% in week 32, 2012 to -19% in week 51, 2011. The average deviation between measured and simulated weekly labour time totals (h week^{-1}) in 18 simulated weeks was 1%. RRMSE is 7% and correlation coefficient r=0.98. The simulation clearly shows the same pattern as the measured data.

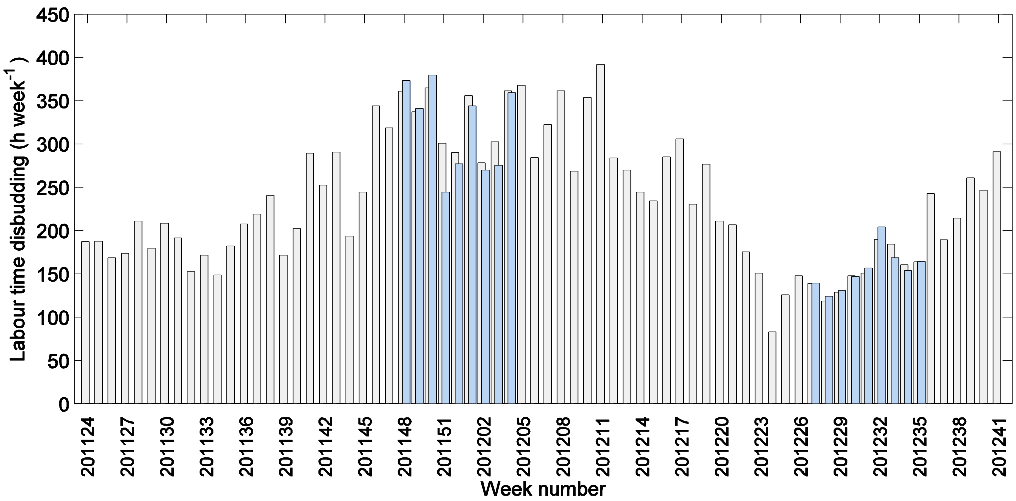

Fig. 5.6 - Simulation results for two verification periods of 9 weeks projected in the measured pattern of weekly labour time totals for disbudding (h week^{-1}) as measured using the labour registration system at Van den Berg Roses, Delfgauw, The Netherlands

Verification results of the process model bending is shown in Fig. 5.7. In simulation, the job-planner planned disbudding over five workdays (Mon, Tue, Wed, Thu, Fri). Execution of bending task was not limited by available time or number of workers. Fig. 5.7a clearly shows that simulated and measured pattern only match reasonably well (r=0.3, RRMSE=30%). This is mainly caused by the smoothened planning in simulation where the bending was executed for the whole greenhouse according to input frequency *f(3,p(d))*. In practice this frequency was less constant as other crop operations compete with bending for resources. In simulation the ratio of weekly operated paths over available paths in the greenhouse (240), ranged 0.94-1.24 and in measured data this same ratio ranged 0.30-1.79. The correlation coefficient between the time series of this ratio was r=0.23. In Fig. 5.7b, the measured and simulated cycle time per path for bending is given. The correlation between time series of the cycle time per path for measured and simulated week results was r=0.97. RRMSE was 8.9%. When workers registered less than one path or more than 10 paths, it was considered an outlier data record. This concerned 16% of the data. Overall measured average was 40.3 and with outliers removed it was 42.6 minutes per path. Average simulated time per path was 43.4 minutes, a +8% and +2% deviation from the measured values respectively. The model predicts the cycle time per path well. Differences in weekly labour time mainly result from differences in resource allocation between practice and the job planner of the model. In this verification, the job planner was not restricted by other crop operations or resource scarcity.

From the verification results it can be concluded that the sub-models for both disbudding and bending function well though the irregular execution of the low priority task bending is not directly captured when other processes are not simulated.

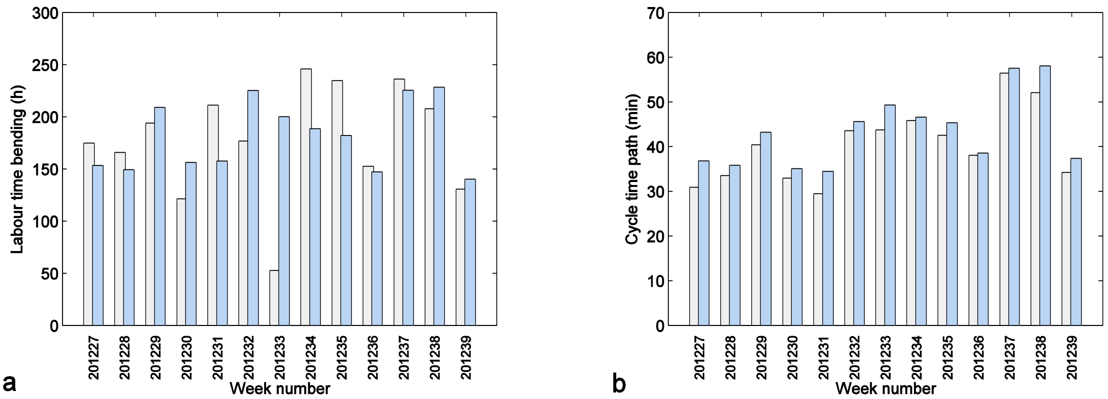

Fig. 5.7 - Measured (grey) and simulated (blue) bending hours per week (a) and cycle time per path (2 subnodes) (b) (minutes). Measured data resulted from the labour registration system at Van den Berg Roses, Delfgauw, The Netherlands.

5.7.2 Scenario simulation results

This Section presents accumulated results of the scenarios given in Section 5.6.1. Prior to presenting scenario results, an example of a single simulated day of the reference scenario S0 is given in Fig. 5.8. Fig. 5.8 shows the time line with the number of workers simultaneously active in the greenhouse in each of the crop operations. Clearly, harvest has first priority, as all worker assigned jobs in this crop operation start at 7AM. Job-entities containing single jobs finish first. These job-entities were split off from the main job-entities. In practice these workers will move to sorting. As soon as the first main job-entity returns, the second priority job disbudding starts, followed by the third operation, bending, after second return to the job distribution centre. On this busy day, the end time for disbudding and bending was reached (18 h), and remaining planned work was skipped to be added to the operational tasks of the following workday.

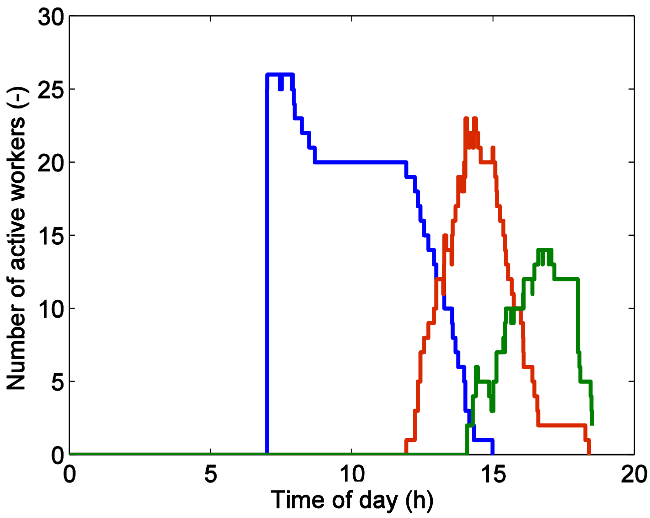

Fig. 5.8 - Simulated number of active workers for a single day in reference scenario S0, August 10, 2012. The time related number of workers active in each crop operation, harvest (blue), disbudding (red), and bending (green).

During the simulation period of 63 days, total measured labour time within the 3 crop operations was 10265 h. With 3.2 million roses harvested, measured labour time was on average 11.5 s per harvested rose, 7.9 s for harvesting, 1.6 s for disbudding and 2.0 s for bending. Table 5.6 shows the simulation results of the scenarios. In scenario S0, 3.2 million roses were harvested in the simulation period and 30240 path sides were processed (20 greenhouse sections, 24 path sides per section, 63 days). For disbudding, 4320 path sides

Table 5.6 - Result of scenario simulations of a 63 days period, July 2nd-September 2nd, 2012. Scenarios: S0 practice, S7 Average workers, number of workers not limited, S2 Permanent team of 35 highly skilled generalists, S1 Low-skilled workers, number of workers not limited, S3 Highly skilled specialists, S4 Generalists, not prioritised for skill, S6 Practice, no job priority, job-entities containing single tasks, S5 Practice, schedule for two crop operations a day.

Scenario	S0 Practice (ref)	S1 Low skilled workers	S2 Generalists	S3 Specialists	S4 Non-prioritised generalists	S5 Two crop operations	S6 Single tasks	S7 Average workers
Worker population (workers)	180	∞	35	63	∞	180	180	∞
Workers (Individual, Average)	I	I	I	I	I	I	I	A
Resources (Limited, Unlimited)	L	U	L	L	U	L	L	U
Worker selection prioritised	Y	Y	Y	Y	N	Y	Y	Y
Labour time *L* (s rose^{-1})	10.9	14.0	9.8	9.0	11.3	12.2	12.3	9.0
%-roses not harvested	0%	0%	0%	0%	0%	0%	15%	0%
Labour costs *C* (€ (1000 roses)$^{-1}$)	47.08	41.39	43.44	40.15	43.35	52.89	52.54	39.86
- harvest (€ (1000 roses)$^{-1}$)	32.76	27.82	29.38	23.76	29.39	32.45	33.01	25.83
- disbudding (€ (1000 roses)$^{-1}$)	7.18	7.49	6.62	8.72	6.27	9.03	8.62	6.75
- bending (€ (1000 roses)$^{-1}$)	7.14	6.08	7.45	7.66	7.68	11.40	10.91	7.28
Sum of late subnodes-Tardiness	12882	14084	6121	5496	6067	4730	9122	6216
- harvest	0	0	0	0	0	0	978	0
- disbudding	2834	5160	774	586	772	1820	2782	560
- bending	9656	8506	5347	4910	5275	2862	5362	5656
Utilisation active workers (mean)	0.70	0.68	0.58	0.39	0.54	0.75	0.68	0.44
- SD of mean utilisation	0.14	0.09	0.12	0.08	0.07	0.15	0.18	0.05
Active workers overall mean	28.1	36.5	30.9	44.7	38.4	30.0	27.0	38.3
- SD mean number of workers	5.61	10.38	5.96	16.59	11.86	4.89	8.37	11.97
- min/max number of workers	20/37	20/56	20/35	20/63	20/59	20/39	3/38	20/63

were processed and 1.7 million disbud actions were executed. For bending 3812 path sides were processed (4630 planned), 0.7 million bend actions were executed (1.1 million planned). With a simulated 10.9 s rose^{-1} scenario S0 shows a bias of -0.6 s rose^{-1} compared to the measured labour time per rose in practice. Labour time was on average 7.4, 1.8 and 1.7 s rose^{-1}, for harvesting, disbudding and bending respectively. The variable labour costs were calculated using the cost factors given in Section 5.6.2. With respect to tardiness, which is expressed as the sum of late path sides (subnodes), multiple counting of late path sides occurs if late path sides are not processed the next day. A late path side contributed to tardiness until it was processed or timed out, thus relatively high totals for this sum occurred. Utilisation was expected to be close to one and for many workers it was. However, the mean in all scenarios was lowered as a result of workers who assisted in the three crop operations only for a short time during peak times (Fig. 5.8). In practice workers spend 30% of total labour time in activities like sorting and packing.

The overall ranks of the scenarios, the ranks per indicator, and weight factors *wf* are given in Table 5.7.

Table 5.7 - Ranking of the scenarios S0 to S7 per outcome and overall ranking. *wf* is the weight factor of an outcome.

Scenario	S0 Practice (ref)	S1 Low skilled workers	S2 Generalists	S3 Specialists	S4 Non-prioritised generalists	S5 Two crop operations	S6 Single tasks	S7 Average workers	*wf*
Overall ranking	6	7	1	3	4	5	8	1	
Performance indicator:									
- labour time *L*	4	8	1	1	5	6	6	1	*1*
- labour cost *C*	6	1	4	1	4	7	7	1	*1*
- %-missed roses	1	1	1	1	1	1	8	1	*1*
- Tardiness of subnodes	7	7	1	1	1	1	6	1	*1*
- Utilisation	1	1	5	7	5	1	1	7	*0.5*
- Nr of active workers	1	5	4	8	6	1	1	6	*0.5*
- SD of means	3	3	1	7	1	3	7	3	*0.5*

With respect to labour time *L*, the scenarios S2 ‘highly skilled generalist’, S3 ‘highly skilled specialists’ and S7 ‘unlimited average workers’ score best. For S7 this is unexpected as it represents equal workers with average company performance. When, compared to S0 and the measured labour time per rose of 11.5 s rose^{-1}, S7 clearly underestimates labour time. With respect to labour costs S1 ‘low-skilled workers’, S3 and S7 score best. This score is different from that of labour time as a result of class dependent labour cost factors. Although S1 has high labour time, costs are low as a result of workers in low skill classes. Scenario S6, ‘single tasks’ takes risks with the harvest operation and loses product resulting in missed revenue. The poor organisation of tasks makes this scenario end last. S6 clearly shows the importance of job-prioritisation. With respect to tardiness S0, S1 and S6 rank lowest. The utilisation seems to make fast teams score low and low-skilled workers score high. This could be a shortcoming of the GWorkS-job planner, which assumes average performance in assigning tasks. Overall S7 with average skilled workers, and S2 with highly skilled generalists share rank 1, followed by S3 highly skilled specialists and S4, unlimitedly available generalists. Despite high labour costs, S5 ‘no more than 2 main crop operations planned for a day’ ranks just above S0. In S5, tardiness is low and labour time for disbudding and bending is relatively high. S0 ranks low because of tardiness, labour cost and labour time.

5.7.3 Discussion

The aim of model based improvement of the operation of horticultural production systems condensed into selection of a best scenario. The aim of the scenarios was to address the questions Q1 to Q4 in Section 0. With respect to Q1, 'Is it profitable to work with low skilled, low paid employees?', scenario S1 clearly shows labour costs are at a high ranking level, but in labour time, tardiness of disbudding and bending and number of workers needed it ranks low. Overall rank is 7, which indicates that it is a disadvantage to work with low skilled workers only. In answer to Q2, 'What is more effective, to work with generalists or specialists?, comparison of S2 'generalists' and S3 'specialists' shows lowest labour time and labour costs for specialists, however utilisation is low and overall mean of active workers and SD of this mean is high. Overall, working with generalists seems more effective. It results in lower labour cost than the reference scenario. Also, generalists show better utilisation, low SD of utilisation and a more stable lower number of workers than the specialists scenario. Tardiness in harvest must be 0 and minimised in disbudding and bending. Both S2 and S3 rank 1 with tardiness mainly occurring in bending, a non-critical crop operation. With respect to Q3, 'Is it smart to reduce the number of crop operations per day?', S5 shows a middle class rank, one position above S0. Reduction of the number of crop operations per day, does not result in less labour time, but tardiness improves strongly compared to S0, utilisation of workers is highest and SD of the mean of active workers is lowest. In answer to Q4 'Does management affect the labour costs and profile of daily labour requirement?', all ranked scenarios show that correct labour management can make a difference in labour time of up to 5 s per rose, and a difference in labour costs of up to 13 euros per 1000 roses (see Table 5.6). The labour cost range represents a margin of € 41,700 for the simulated greenhouse of 3.6 ha in the simulation period with 89 roses harvested m^{-2}, which is equivalent to 7.1 € m^{-2} per year. Compared to the reference S0, the largest improvements in labour time were -17.5% for specialists S3 and -10% for generalists S2. S6 'single tasks' is a clear example of poor management. Labour management can affect the annual profile of daily labour requirement, by reducing SD in worker utilisation and SD of the mean of number of active workers. At this point the generalists scenarios S2 and S4 rank best, followed by the reference scenario S0, S1 and S5. S7 shows that simulation based on average workers in this case underestimates labour time. Individual abilities are not represented in scenario S7, while neglecting capacity limitation may lead to false results (Jahn et al., 2010). Also in S7, uncertainty in initial average skill and simulation with averaged skill parameters may have introduced inaccuracy in company performance.

In Section 5.4.3 four assumptions with respect to individual learning curves are stated. The learning curve was construction based on literature and harvest performance. It is uncertain if learning curves are equal for all crop operations and it is uncertain if personal potential is enough to capture individual learning curves. More advanced registration of experience and performance of individual workers in labour registration systems would be relevant from this perspective. Currently data are lacking for more accurate definition of learning curves. In Section 5.6.2 labour cost factors are assumed and best scenarios were selected based on classification of model output and weight factors. The cost factors fit current collective labour agreements, but in practice they differ between growers. Even though the assumptions were selected for a close match with reality, they may affect model output. The studied period, July and August, is considered indicative for longer periods because even though daily labour time per process differed strongly, Van den Berg roses managed greenhouse climate for constant yield. The cumulative yield curve over 482 days was linear with intercept 0 and slope $\pm$1.5 roses m^{-2} per day (R^2=0.999). The measured cumulative labour time curves were approximately linear with R^2>0.97.

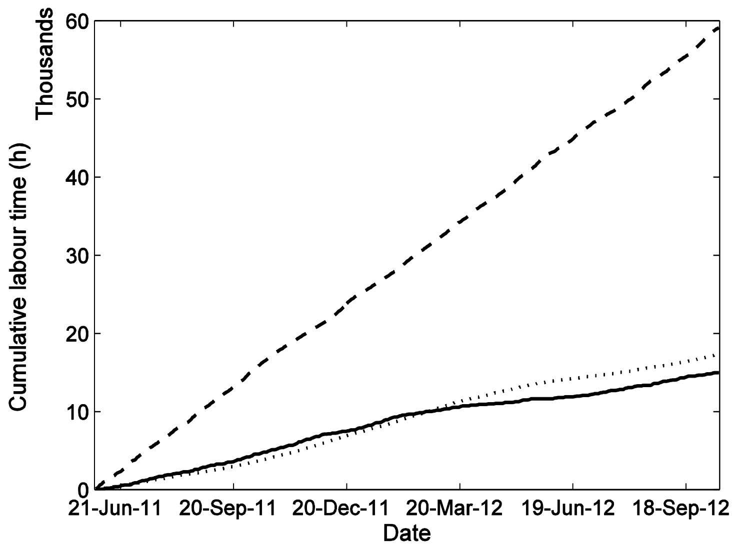

Fig. 5.9 - Measured cumulative labour time in hours at Van den Berg Roses, Delfgauw, The Netherlands for harvest (dashed line), disbudding (dotted line) and bending (solid line).

The results of scenario simulations must be interpreted as indicative rather than as an absolute ground truth. Overall the model simulates very well integrated crop operations in different scenarios including scenarios with parallel execution of different tasks in one greenhouse section. The job planner assigns crop operations to workers based on straightforward operational planning and average performance estimates of workers. Simulation performance could improve further if individual performance and constraints of workers with respect to the labour agreement is known to the job planner. Currently no crop effects can be tested as the model works with measured crop data. The scenario assessment could benefit from replacing the empirical multi-objective ranking system with model based optimisation of crop operations. An example of model based optimisation of technical systems is given in Hubscher-Younger, Mosterman, DeLand, Orqueda, Eastman (2012).

5.8 Conclusion

The GWorkS model (Van 't Ooster et al., 2013) was adapted to simulate the crop operations disbudding and bending in a static growing system for cut-rose without altering the generic model structure. The model verification showed that the adapted model performed well for bending and disbudding. Also, the model was successfully extended for full scale simulation of a greenhouse, for resource limitations and for individualisation of worker properties. The work scenario study showed that model based improvement of crop operations is a real option in preparation of new management strategies. The scenario study answered research questions effectively and quantitatively. The study pointed out that working mainly with low skilled, low paid workers should not be recommended. Specialised workers were most time effective, but a permanent team of highly skilled generalists ranked best. In case the number of crop operations per day is reduced, the model result is almost indifferent when compared to the reference, although labour organisational outputs improve. Choices in labour organisation resulted in differences between all scenarios of up to 5 s labour time per cut-rose for the three crop operations, harvest, bending and disbudding and an estimated range 7.1 € m^{-2} per year in labour costs for the three crop operations. The largest improvements in labour time compared to the reference were -17.5% for specialists and -10% for generalists. Working with non-prioritised single tasks on all crop operations was indicated as a clear example of poor labour management. Substantially simultaneous execution of tasks results in a realistic allocation of workers and equipment. Overall, the GWorkS-model provided clear answers to the research questions using the full complexity of crop operations. Effects of labour management scenarios and focus points for improvement were exposed.

5.9 Acknowledgements

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Chapter 6

Conclusions, General discussion and Recommendations, Future perspectives

A. van ’t Ooster

6 Conclusions, General discussion and Recommendations, Future perspectives

This Chapter presents in Section 6.1 the general conclusions in view of the main objective, the research questions and the model requirements set in Chapter 1. In Section 6.3 a general discussion and recommendations for future research are given. The discussion elaborates research results not yet or limitedly discussed before, or relevant for use of the method. Section 6.4 discusses future perspectives for applications of the model-based method.

6.1 Conclusions

The main objective of this research was to "*obtain good and quantified understanding of labour and crop operations in horticultural production systems materialised in a generic model-based method".* In view of this objective the following is concluded. This study demonstrated that greenhouse crop operations may be characterised as a discrete event system in which operator actions are identifiable as a chain of events. Discrete event simulation, as implemented in the GWorkS model, described greenhouse crop operations mechanistically correct and predicted labour use accurately. The model was first developed and validated for harvesting one crop loop in a mobile cut-rose system by one or two operators (Chapter 2). A one month validation showed that harvest labour time accuracy was 92% and RRMSE was 18%. The model exposed effects of internal parameters that were not visible in acquired data, as was illustrated for operator and gutter speed.

The generic approach of the modelling concept was tested by transferring GWorkS from harvesting of a mobile growing system to harvesting a greenhouse section in a static growing system for cut-roses and one or two harvest cycles per day (Chapter 3). When extended with the specific properties and process elements of a static growing system, the model results were compatible with those obtained with the mobile system. In a one week validation, simulated and measured mean labour time were 3 h 59 min and 4 h 2min respectively, RRMSE was 4.4%, and r=0.99. In a 3 months validation, a parameter set based on the average operator performance in the company explained the mean and standard deviation in a data set on labour time accurately, however RRMSE was 15.2%. Analysis of the mean square deviation (MSD) of measured and simulated harvest labour time and harvest rate showed that more than 90% of RRMSE could be explained from pattern deviation within the time series, mainly resulting from performance differences between workers. The increased RRMSE could therefore mainly be explained from the absence of individual harvester parameters in the model.

In the Chapters 3 and 5, model-based assessment of scenarios was demonstrated. The model was successfully used in a scenario study on the crop operation harvest of cut-roses

(Chapter 3) and in scenarios for integrated evaluation of three crop operations, harvest, disbudding and bending (Chapter 5).

The work scenario study in Chapter 3 quantified the effect of worker skill on labour performance. For rose yields of 0.5 and 3 harvested roses per m^2, the harvest rate was 346 and 615 stems h^{-1} for average skilled harvesters, 207 and 339 stems h^{-1} for new harvesters, and 407 and 767 stems h^{-1} for highly skilled harvesters, respectively. The model indicated economic feasibility for labour management and worker skill. Simulations pointed out that working with electric trolleys is more time effective than working with hand pushed trolleys, but economic feasibility of electric trolleys could not be proven. A second harvest cycle in one day in rose is only feasible if yield quality effects would compensate for the 0.2-1.1 euro cent extra costs per harvested rose.

Sensitivity analysis in Chapter 4 pointed out the importance of model parameters as well as that of output uncertainty. The model was not extremely sensitive for any of the 22 tested input parameters and individual sensitivities changed with crop yield. The highest sensitivity in terms of labour time or throughput yielding a normalised sensitivity coefficient greater than 0.1 was found for greenhouse section length and width, rose cutting performance, trolley speed, anticipation distance before cutting, yield, and number of harvest cycles. The main sources of model uncertainty were found in parallel execution of actions and trolley speed. As a result, the coefficient of variation and the 99% uncertainty range was relatively large for accumulated transport time and overlap time. The uncertainty effect of these parameters on labour time, throughput and utilisation of the operator was acceptably small with CV < 5%.

The integrated scenario study on harvest, disbudding and bending in Chapter 5 showed differences between scenarios of up to 5 s per cut-rose in simulated labour time and up to 7.1 € m^{-2} per year in labour costs. The model performed full scale simulations of a greenhouse with restrictions on available workforce and equipment, and with individualised worker properties. The simulated practice of the grower and the simulated minimum cost scenario indicated possible savings for a grower of 4 € m^{-2} per year, that is 15% of the labour cost total for harvest, disbudding and bending and close to 150 k€ per year for the studied greenhouse. The scenario study was able to answer several research questions on labour management and staff composition quantitatively using a multi-factorial criterion. Thus, model-based improvement of crop operations is a real option in preparation of new management strategies.

The first generation model-based method was developed and validated by means of data acquired at commercial growers. All underlying sub-models on harvest, disbudding and bending were verified. It may therefore be concluded that the objective of the research was realised.

To the best of our knowledge, the GWorkS-model is the first model that is able to simulate the crop operations in a greenhouse in one simulation taking into account the available resources and staff.

6.2 Reflection on model requirements

In support of the conclusion we reflect on the requirements for the model-based method mentioned in Table 1.1, Chapter 1, to evaluate if the requirements are met. These requirements guided the making of GWorkS and were realised in Chapters 2-5.

The model-based method is able to support growers and designers in analysis and evaluation of design concepts for system innovation (req. 1), but effects of innovations were reserved for future research. Contributions to interpretability, manageability and traceability of effects of labour organisation changes (req. 2) were shown in Chapter 5. The Chapters 3 and 5 showed that feasibility evaluation (req. 3) and multi-factorial assessment by simulation is a good option to test and evaluate changes in work methods. The Chapters 2-5 all give clear expression to the event based nature of crop operations (req. 4), as the core of GWorkS is an event based queueing network. The system evaluation requirement that the model should be generic in order to support design effort (req. 9) was partially fulfilled as the model-based method has limited freedom in defining the crop production system. The structure and setup of the model is generic where possible and system specific where inevitable. This enhanced model flexibility and model applicability for system improvements in different growing systems.

With respect to the system definition requirements (5-8), greenhouse layout is parametric but restricted to the rectangular shape (req. 5.1), greenhouse partitioning in greenhouse sections, in definition of paths, locations and size of main aisles as well as of the cultivated areas is parametric. Therefore, freedom of layout design, req. 5.2, is realised. Concerning crop cultivation systems (req. 5.3), both mobile and static systems may be defined, but routing options for mobile cultivation systems were restricted to crop loops as used in the mobile rose cultivation system. Freedom with respect to crop operations (req. 5.4) is high. For each action type the service time was described by a probability density function and each single action carried a three dimensional coordinate to identify the location of the action. For harvest and disbudding sequential processing of single path sides was implemented. For bending a choice between sequential processing of single path sides or simultaneous processing of both sides was implemented. In case crop operations in the greenhouse must be extended with (product) processing steps, as for instance the sorting of truss tomatoes in boxes, this will need sub-model extension. The model provides high flexibility at this point because sub-models are substitutable. Sub-models with a more or less detailed system description depending on the design or evaluation problem at hand may be implemented but will require (some) modelling effort. In Chapter 5 the requirements 5.5-5.7 on model flexibility with respect to actors and individualised actor parameters were realised. Different crop operations were modelled and validated (req. 6). In all cases the performance was good to very good or differences could be explained from task planning differences between the model (regular) and practice (irregular) as shown in Chapter 5 for bending. Planning of operations (req. 7) was realised, however optimisation of job planning was not implemented yet. Claassen, Hendriks and Hendrix (2007) present several decision techniques such as linear programming to improve the value of the model-based method for growers. The GWorkS-model exposed effects of labour management scenarios (req. 8) and focus points for labour management improvements (req. 10).

System analysis requirements (req. 10-13) with respect to operational details, system levels and sensitivity analysis are considered fulfilled, however faster simulation is required. The requirements with respect to the model output (req. 14-16) were all realised. General conventions and key indicators originating from operations research and factory physics (Hopp & Spearman, 2008) were implemented in GWorkS, thus allowing control and evaluation of horticultural operations analogue to those used in operations research in industry.

The future success of this modelling approach depends on its embedding in operational research in greenhouse horticulture and its application in the development of greenhouse production system innovations. In order to predict, next to cost effects, also crop production responses and net financial result, the method would benefit from interaction with greenhouse climate and crop growth models.

6.3 General discussion and Recommendations

Results generated by the model-based method gave indications of the strengths and weaknesses of the approach.

Strengths: Currently greenhouse crop operations in cut flower and vegetable production mainly use manual labour for treating plants as a result of a complex unstructured environment of the greenhouse crop. Most of this labour is characterised by repetitive actions (Gay, Piccarolo, Ricauda Aimonino, Deboli, 2008; Callejón-Ferre, Pérez-Alonso, Carreño-Ortega, Velázquez-Martí, 2011). Scenario simulation supports analysis and re-engineering of existing processes by identifying and eliminating bottlenecks and process defects. Simulation also supports evaluation of the performance of a design concept in terms of its ability to meet growers needs. These main functions were addressed in Chapters 2-5. Many of these functions are used in industry as well, for instance in total quality manufacturing (Hopp & Spearman, 2008). The GWorkS-model has a parametrically defined greenhouse layout, crop cultivation system layout, and allows selection of crop operations and output of interest. This provides a strong basis for examining variants of crop production systems for different aspects like production scale, crop yield, frequency of crop operations, number of workers/actors, choice of resource types, and of resource properties for their effects in both key performance indicators and in timed signals of actions.

Weaknesses: A clear weakness of the model-based method is the need to have data for an accurate and representative simulation. For example, crop status data such as daily yield are now a model input and need to be acquired for each crop type investigated. Parameters on actions not in the library must be measured in practice for existing actions and estimated for newly designed actions. In the sections 6.3.2 and 6.3.3 other options for acquiring these data are discussed. Another weakness is the elapsed time in long simulations containing many events such as the ones presented in Chapter 5. It is recommended to investigate and improve simulation speed in order to make Monte Carlo analysis as performed in Chapter 4 an acceptable operation, also for longer and more complex simulations. A practical weakness is the limited model readiness and lack of an intuitive user interface.

6.3.1 Model performance and model accuracy

In system design and development, effective and feasible systems must be realised. In implementation an entrepreneur wants to have proof of the feasibility of his investment. In Chapter 3 it was stated that the model should aim for a 10% accuracy or better. The model results in Chapter 2 and 3, and 5 showed high model accuracy for labour time in current cut-rose systems. The model satisfies the required accuracy because bias of the mean in measured and simulated time series was under 6% in all cases. The relative root mean squared error (RRMSE) for time series of several weeks to months was in general between 10 and 20% for harvesting, under 10% for disbudding, and 30% for bending. In all cases with RRMSE above 10%, the differences did not originate from bias of the mean or bias of the standard deviation, but mainly from differences between labour management and resource constraints in GWorkS and in practice, which resulted in a different pattern in time in the measurements and simulations.

In the sensitivity analysis (Chapter 4) it was stated that significance of difference between scenarios should be proven for real differentiation between solutions. Monte Carlo simulation allowed this by comparing probability densities of model outputs based on input uncertainty. For higher input accuracy it is easier to prove that difference between solutions is significant. As a minimum, the model-based method should target higher accuracy than the accuracy of the assessment by experts to improve decision quality both in development of innovative systems and in selection of solutions. However, the accuracy range of input estimates performed by designers or growers is unknown. The targeted output accuracy of the simulation model should also be better than the realised accuracy with analytical spreadsheet based models such as the ones used by Gieling, van Henten, van Os, Sakaue and Hendrix (1996) and Pekkeriet, Hemming, Bontsema, Saeys and Hočevar (2014). Though expert accuracy cannot be measured easily, comparison of expert evaluation with simulation results and measured results in existing crop operations is recommended.

The importance of model input accuracy was demonstrated in Chapters 3 and 5 in simulated scenarios that were based on uniform worker properties. In Chapter 3, the parameters representing the average operator performance in the company, accurately explained the mean and standard deviation of labour time use of a measured data set. In the average worker scenario in Chapter 5 however, video observations of volunteering workers did not represent the company average. An underestimation of the company labour time of 22% resulted, since the more skilled workers volunteered for video observation. This illustrates that input accuracy is important for reliable and representative results. Effects of input uncertainty on output uncertainty were discussed in more detail in Chapter 4.

6.3.2 Use and acquisition of probability density functions for human handling

Video observations in practice evidently showed a lognormal distribution shape on the duration of basic repetitive worker actions. QQ-plots and confidence intervals of the probability density function (pdf) parameters, mean μ and standard deviation σ of the variable's natural logarithm, confirmed the validity of this assumption for several video observation data sets. The probabilistic description for basic human actions introduces a natural variability in the execution of actions. In case many repetitions of an action occur (>1000), the mean duration converges to the expected value. In simulations covering long time periods on sequential actions with high pdf sampling rate, and a user with interest for cumulative output only, the use of pdfs may theoretically be omitted. However, in the more common case of (partial) concurrency of actions the use of pdfs is required, since partial parallel execution of actions manifests as a variable cut-off filter as shown in Chapter 4. Although pdfs require more detailed observation of human action in crop operations, they were maintained in GWorkS for all time scales because in all cases parallelism occurs and pdfs describe low system level characteristics better than the expected value of a stochastic variable $E(\nu)$ alone.

Video observations were used to acquire pdf parameters on human action in crop operations. Subjects of observation were workers, equipment, plant geometry and environment. Elements of human motion are generic, but have many degrees of freedom and depend upon anthropometrics. This means that the human motoric model, fineness of movement and crop geometry, are the major factors influencing the resulting parameters of the pdfs. This is illustrated by the pdf-parameters μ and σ of a seemingly equal action 'cut rose' in the mobile system, where the worker acts on one row of plants, and the 'cut rose' action in the static system, where the worker acts on two rows of plants. The parameters μ and σ of these actions differ as shown in Chapters 2 and 3, with μ=0.237, σ=0.545 (n=916) for the mobile system and μ=1.305, σ=0.361 (n=1517) for the static system. If mean and variance of the duration of an action are available, than the pdf parameters of the lognormal distribution μ and σ, being the mean and standard deviation of the variable's natural logarithm, are determined as well. In order to find service time mean and variation of basic actions in crop operations, it is recommended to explore existing databases on work studies such as AgroWerk (De Jong, van Raffe, Roelofs, Schreuder, 2007) and the underlying time study records to derive pdf-parameters without the need for video observation and processing (in Noldus Observer XT).

Currently, practical labour registration systems do not register data at action level. Accurate estimation of the variance of actions based on data of current labour registration systems is therefore not possible. The scenario to be simulated and the required accuracy are leading in the decision for additional observation of basic actions. In order to obtain accurate input parameters on pdfs faster, it is recommended to speed up the time consuming acquisition and (manual) evaluation of footage and to decrease the influence on the worker of the measurement itself. To speed up the analysis of footage, it is recommended to add motion tracking data to Noldus Observer XT10 software or to analyse actions based on motion tracking sensors alone (Zhou & Hu, 2008). Examples of camera-less motion tracking sensors are XSense MTI (Suh & Park, 2009) with 3 axis accelerometers, gyroscopes, and magnetic sensors, and the XSense MVN motion capture suit for full-body, camera-less inertial motion capture (Roetenberg, Luinge, Slycke, 2009), both using wireless data transmission. This technology could be used for more detailed data acquisition than labour registration and video recording with less risk of influencing worker performance, and with a decreased effort to acquire data. Another promising option for faster capture of human performance data, described in the framework of probability density functions on human actions, is computer vision-based detection, recognition and interpretation of human actions (Moeslund, Hilton, Krüger, 2006; Turaga, Chellappa, Subrahmanian, Udrea, 2008; Poppe, 2010). It is recommended to further explore these techniques in future research in order to decrease the data acquisition effort for new model applications and the maintenance effort for current applications.

6.3.3 From cost to profit evaluation - Interaction of crop and human handling

The GWorkS-model uses measured crop data and is therefore inflexible with respect to predicting yield effects, revenue and profit effects of crop operation scenarios. This was made clear in Chapter 3, where cost effects of two harvest cycles were quantified, but effects in revenues could not be determined. One motivation for using SimEvents® as the underlying discrete-event simulation engine for GWorkS was that it enables co-existence of continuous time-driven components and event-driven components in hybrid systems. Vanthoor, de Visser, Stanghellini and van Henten (2011); Vanthoor, Stanghellini, van Henten and de Visser (2011); Vanthoor, Gázquez, et al. (2012); Vanthoor, Stigter, et al. (2012) defined a model-based greenhouse design method in Matlab with dynamic evaluation of the greenhouse climate and crop yield response for tomato. Crop operations that influence the sources and sinks for assimilates will affect crop growth and probably also the yield and profit. It is recommended to quantify these effects to determine the relevance of hybrid modelling. If relevance is proven, a hybrid system could emerge from the GWorkS-model and the model of Vanthoor (2011) as a next step towards a model-based method to predict and (economically) optimise greenhouse design, climate engineering, crop operations and crop production. For the GWorkS-model alone this would mean that not only cost effects resulting from process operation and process management become apparent, but also revenue changes as a result of these crop operations would show as well as effects of task frequency, thus potentially improving options for system optimisation.

Another recommended function would be interaction with morphological models of crop growth and development (Buck-Sorlin et al., 2011). These models can provide exact locations of pruning and harvest actions and spatial differences in crop status, thus decreasing the use of stochastic variables with respect to action locations. Also these models seem to provide good options to include yield effects of crop operational interference in crop growth. Prediction of crop response to human handling would be a prerequisite to also predict the need for crop operations. This would enable optimization by identifying trade-offs and by maximizing profit. Seginer (1989) and Van Henten (1994) already presented management and control strategies on aerial environment for best crop production and best economic result.

6.3.4 Crop operations as a discrete event system - use of DES

Crop operations in greenhouses were approached as a discrete event simulation problem. In Discrete Event Systems (DES), an event calendar processes all future events in the ascending order of their scheduled time (Clune, Mosterman, Cassandras, 2006). The combination of Matlab®, Simulink® and SimEvents® allowed effective implementation of the GWorkS-model. It was shown in Chapters 2-5 that the GWorkS modelling and simulation was successful. A small additional advantage of SimEvents® is that the graphical environment enhances the readability of the model because of its good options to make the system implementation in SimEvents® resemble the underlying IDEF3 process model.

A drawback of DES is that entities are passive objects in a flowchart or queueing network. Actions are always defined in the decision structure of the flow chart. To clarify this point, one might think of the analogy of a river network and a floating wooden shoe. At a river branching, the shoe has to be actively pushed to make it move to the right branch (or the left), or its path will be decided by properties of the river such as size of branches, or the probability that the strongest current is directing the shoe right (or left). So, the wooden shoe is passive and does not influence the decision itself. Though in GWorkS, entities were given individual attributes including pdf-parameters, behavioural rules were flowchart implemented. A consequence of the inability of entities to carry methods is that standard DES pdf-function blocks had to be replaced by Matlab code for entities that carry their own pdf-parameters and needed sampling from 'private' pdf's in one function. In greenhouse crop operations workers or intelligent systems are active objects, making autonomous decisions, with individual behavioural rules, and with direct or indirect interaction. It would make sense to have entities representing active objects that contain methods. An alternative model paradigm for the GWorkS-core could be to define actors as active independent and interacting objects with properties and methods of their own. This paradigm represents the modelling approach of agent based modelling (Borshchev & Filippov, 2004). It is recommended to explore the benefits of agent based modelling in a separate study.

6.3.5 Level of detailing crop operations and human behaviour

The GWorkS-core as it was used in Chapter 5 included multiple crop operations and constrained resources, that is a limited number of workers and equipment per operation. Crop operations were defined as sub-models at the level of detail needed. A sub-model may be anything between a server and a detailed multi-layered subsystem defining the crop operation to the detail level required for testing a re-engineered crop operation in a crop cultivation system. A framework for several types of substitutable sub-models was defined. The required depth in the system hierarchy necessary to describe a scenario, decides what model type prevails. For example, if time and resource allocation of a crop operation is relevant, but no detailed information is required on the process, then a simple model with an adequate characterisation of the cycle time of a path (side) is satisfactory (high aggregation level). Also in some cases of long term simulation a high aggregation level is an option for faster simulation. In case action details within a scenario are to be simulated, then the model is seamlessly expandable (low aggregation level). For example, when the task 'Review rose' is performed by image processing, a system hierarchy defining service times for image acquisition, data processing, decision making, and subsequent action with probability for failure and trials of action would be an in depth extension of a current definition of a human action. Currently the crop operations in GWorkS are detailed to the level of basic human actions. To be effective in simulating and optimizing the use of new technology in greenhouses, it is in some cases necessary to replace system elements defining the human action with elements defining the intended functionality of the automation solution. In view of this perspective the GWorkS-model follows a generic, flexible system hierarchy.

6.3.6 Resource selection, allocation and interchangeability

The GWorkS-model simulates crop operations executed by workers under scarcity of workforce and material resources (Chapter 5). The operational labour capacity is then constrained by the available number of operator units. Also properties of workers and resource types are model constraints. Availability of the required resources is a condition for executing a task. Resources are managed by a resource pool which was introduced to allow job-entities to select and allocate resources. Work is delayed if a required resource is not available. Composite entities join all required entities in one place at one point in time for execution of an action. If a composite entity is generated all constraints are satisfied and the corresponding task is executed. This generic approach allows flexibility by (partial) substitution and interchangeability of resources. Thus a mix of differently equipped workers could be active in one or more crop operations.

Workers were selected based on skill. Equipment was selected based on type and capacity. Prioritisation of resources is potentially possible for any subset of resource attributes, for instance a role property and a cost factor. In priority mode, the resource which fits the criterion best, is selected. In standard mode, the first available resource is selected. In GWorkS, this selection method represents the manager and supervisor knowledge and action. Selection may be based on individual authorisation, variable costs, availability in time, and performance properties. Individualised attributes are commonly used in Agent Based Modelling (Borshchev & Filippov, 2004; Owen, 2013). This generic selection method based on individual properties allows the GWorkS-model to select also between operators of different type, such as workers using different equipment, or human workers versus autonomous robotic workers. Proof of principle for the selection method was given in Chapter 5.

6.3.7 Scheduling of crop operations

In GWorkS, the scheduling of crop operations is a crucial function, performed by the job-planner (Chapter 2 and Chapter 5). Currently the job planner uses job status and job history in matrices as well as expected actor performance and planned duration of a process to allocate resources to nodes scheduled for processing. The feedback from the GWorkS discrete event simulation core provides the job planner with the execution status of tasks at completion of a workday. Simple matrix operations not only determine the daily tasks and the task locations in each operation, but also set the task priority, transfer incomplete tasks of the previous day, and time out obsolete tasks. More advanced decision methods as used in the discipline of operational research and decision sciences (Claassen et al., 2007) such as linear programming are recommended for further research. Decision science methods help to optimise planning for minimal labour time or minimal labour costs, and to improve the match between task planning and task execution (Gu, Goetschalckx, McGinnis, 2007), to prevent voids in a worker timeline, to optimise transport (Vis & de Koster, 2003; Dotoli, Fanti, Mangini, Stecco, Ukovich, 2010) or to improve task allocation to complete operations in the shortest time possible and to use resources to their full potential (Annevelink, 1992). It is recommended to include expected return in case the task is executed or missed revenues in case the task is timed out. These methods are especially relevant in case workers or devices have insufficient capacity which results in incomplete execution of tasks.

6.3.8 Practical value of the model for growers

Many Dutch growers use labour registration systems. Unfortunately, growers do not use these data to their full potential. A practical achievement of this research was that growers contributing to this research started to use their data more actively for operational management and were enthusiastic about it as it provided better control of operational processes, both with respect to effectiveness and leanness. The level of detail in many registration systems is not enough to fully support development of models like the GWorkS-model. Additional more detailed observations are needed to obtain descriptive parameters for actions in crop operations, as discussed in Section 6.3.2. Manufacturers of labour registration systems should be encouraged to extend data registration to enable time and work studies and to facilitate basic data analysis for growers. The GWorkS model enables planning and simulation of labour scenarios. In Chapter 5, several labour scenarios performed better than the practical reference scenario. It indicated promising first steps of practical usage of the information resulting from the GWorkS-model such as support of planning and evaluation of crop operation execution by virtual experiments. From a scientific viewpoint, it indicates that modelling with corresponding virtual experiments could contribute to labour efficiency in practical crop operations.

6.4 Future perspectives for applications of the model-based method

The future perspective of the GWorkS-model is discussed in view of the purpose and future application of the model.

Horizontal extension of GWorkS to other crops: The GWorkS-model was developed for path based crop cultivation systems and rotating loop systems holding plant batches on movable units with operators performing crop operations at one location for the case of cut-rose. However, these types of crop cultivation systems are used in many crops, cut-flowers, potted plants, and vegetable crops. Application of GWorkS in other crops is a small step as proven in Aantjes (2014). The main issue is the acquisition of input parameters for each crop (Section 6.3.2) and crop system specific parameters.

Interaction of crop reaction and human handling by means of hybrid system simulation: Synergy between the discrete-state model, GWorkS, and continuous-state models on greenhouse climate (Vanthoor, Stanghellini, et al., 2011) and on (morphological) crop growth (Buck-Sorlin et al., 2011; Vanthoor, de Visser, et al., 2011) could add to system flexibility and to the value of the results in terms of optimisation of net profit, prediction of production and timely delivery of products. However, as discussed in Section 6.3.3, only if future research provides proof of this added value, this perspective is worthwhile to continue to pursue.

Optimisation of job scheduling and resource allocation: A relevant future application of GWorkS is to find shortest operation times and best performance from resources available for maximized labour efficiency, minimized cost and resource use, or for realising a permanent skilled team in a desired annual profile of labour demand. Resource selection is based on individual properties. Optimisation of job scheduling and resources allocation is a logical future perspective. With the number of selected actors being an integer number, a genetic algorithm for mixed integer optimisation would be a logical choice. Both, Zelenka (2010) and Hubscher-Younger, Mosterman, DeLand, Orqueda and Eastman (2012) suggest use of a genetic algorithm to determine optimal resource allocation and optimal job scheduling. Lu, Lam and Dai (2008) present discrete event simulation to complete construction projects in minimum time while extracting the most efforts from the resources available by means of resource-constrained critical path analysis and particle swarm optimization.

Support of operational management of growers: As demonstrated in the Chapters 3 and 5 the model compares operational management scenarios effectively. A possible future application of the model would be to support growers in operational management by means of daily labour planning and simulation and animation of work methods and scenarios. Also organisations delivering consultancy services to growers or companies delivering operational management support systems could apply GWorkS or parts of it for planning and scenario evaluation.

Simulation of future scenarios and supporting the design of intelligent systems for greenhouse automation: The GWorkS-model has a potential to support design effort in research, internal logistics and automation industry. Though not yet effectuated, this thesis project anticipated the use of intelligent systems for (partial) automation in greenhouse crop operations. An example of upcoming technology is the development of intelligent robotic systems for crop operations (Bac, Henten, Hemming, Edan, 2014). Autonomous navigation on rails is commonly accepted (Dahl, 1994), navigation independent of predefined paths progresses strongly (Yavuz, 2007). Bechar and Edan (2003) and Bechar, Edan and Meyer (2004) indicate man-machine collaboration as the most likely development for the near future. Kulic and Croft (2006) and Zanchettin, Bascetta and Rocco (2013) investigated human-robot interaction to enable co-existence of humans and robots in one workspace. Kruse, Pandey, Alami and Kirsch (2013) published a survey on human-aware robot navigation. Technological innovation may support individualisation of plant treatment, product quality improvement, product diversification and production timing.

When embedded in crop operations, sensor and information technology can potentially improve both the worker performance and crop production performance. Sensor technology which operates outside the human physical senses enhances the ability to determine crop and product status. Examples are photosynthesis activity sensing (Van der Tol, Verhoef, Rosema, 2009), and early disease detection (Jansen, 2009), hot and cold spot detection. This technology may find a place in support of planning and execution of crop operations. Wearable electronics, augmented reality and ambient intelligence (Cook, Augusto, Jakkula, 2009; Bautista-Hernández & Ramos-Quintana, 2013) allow interaction between workers and corporate information, guidance of workers, and monitoring of worker and greenhouse performance. The introduction of in row sensing and information exchange is still in an early stage.

Collaboration with developers of intelligent systems for innovation of crop operations is an important future perspective for GWorkS. To be effective in simulating (and optimizing) the use of new technology in greenhouses, it may in some cases be necessary to replace the system elements defining basic human action with elements defining the intended functionality of the new solution. The generic model approach already allows flexibility by (partial) substitution or addition of resources. Thus workers may use new equipment, or substitutes for workers may be introduced to allow a mix of workers and robots to be active in crop operations.

Future crop operation scenarios might consist of new work methods using augmented reality, or work methods with separated tasks for human and robots, or human-robot collaboration. An example of augmented reality could be a monitoring system which points out actions in crop operations, for instance by indicating the product to be harvested. The intended result would be an objectively determined quality of the harvested product, in-field quality classification, no harvest of raw product, faster actions because the action is pointed out in advance. Intelligent systems have the potential of raising the fresh product quality, lowering production costs, and reducing the drudgery of manual labour (Bechar & Edan, 2003). Intelligent systems for automation of crop operations are under development (Bac et al., 2014), but best operational scenarios and best crop monitoring are yet unknown. Simulation allows numerous experiments to find implications of adaptations in crop operations. It is the challenge for the near future to find added value for greenhouse horticulture through advanced technology by monitoring crop, by tuning crop operations and by obtaining best product quality with less hours of manual labour.

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Summary

In Dutch greenhouse horticulture, labour is a main cost factor, which represents 25-30% of the production costs. During the next decades, improving labour efficiency in horticulture will be as important as ever to stay competitive on the (inter)national market. However, decisions on introduction of new technology, like vision and robotics, and modification of the production system are not easily made. Growers require reduced production costs, a maintained or improved production level, a maintained or improved product quality, and secure investments to stay competitive. The current innovation challenge is to realise a higher labour efficiency in crop operations. However, the crop and its environment are complex and analogy with the industry is not strong. Only when design concepts pass a quantitative evaluation before implementation, the risk of failure for growers can be reduced. System analysis for an effective embedding of new technology in crop operations is not yet conducted with quantitative models.

It was the ambition and objective of this research to initiate and develop a model based method that can be used to analyse labour in crop production systems and to quantify effects of system changes in order to increase the success rate of systems innovations. Such a method is also valuable for decision support in case the system change concerns a change in labour management strategy. The societal objective of this research was to contribute to effective greenhouse crop cultivation systems with efficient use of human labour and technology. In this project, the initial version of this model based method was designed and developed. The resulting model was named GWorkS, an acronym for Greenhouse Work Simulation. A quantified understanding of labour in crop operations in horticultural production systems resulted. The method allowed simulation of existing greenhouse crop production systems, analysis of improvements, and identification of bottlenecks in operational processes. Envisaged solutions could be quantitatively evaluated without having to first build them. Model based evaluation of labour in crop operations is relatively new in Dutch greenhouse horticulture. Being more accepted in industry, model based evaluation of manufacturing systems in industry served as a source of inspiration.

The research was focussed on cut-rose production, a crop that was considered representative for many cut-flowers and fruit vegetables. The focus in *Chapter 2* was to simulate the actions of one or two workers harvesting roses on a moving gutter of an automatically rotating gutter system at one location on the main aisle. The mobile rose systems were designed to increase labour efficiency. However, many questions remained on settings of operational parameters for best performance. A queueing network model,

GWorkS-rose, was presented for simulation of labour processes in a greenhouse with a mobile rose cultivation system. The objective was to quantify effects of production system changes by means of a flexible and generic model approach. Data from a state-of-art mobile rose production system was used to validate and test the GWorkS-rose model. System performance was simulated and compared to the measured performance. Results of a single day validation showed that the model estimated harvest labour time with an accuracy of 94%. For a one month validation an accuracy of 92% and RRMSE of 18% resulted. The value of RRMSE was caused by missing data, such as the number of workers at the loop and the actual gutter speed. The model exposed effects of internal parameters not visible in acquired data as was illustrated for operator and gutter speed at different rose yield levels. It was concluded that the model can be used for studies on design and management of this kind of production systems. The structure and setup of the GWorkS model was made generic where possible and system specific for the mobile rose cultivation system where inevitable. This approach enhanced model flexibility and applicability in other growing systems.

In *Chapter 3*, the generic approach of the modelling concept was tested by transferring GWorkS to harvesting a greenhouse section in a static growing system for cut-roses with one or two harvest cycles per day. The adaptability and transferability of the model concept was proven and specifically validated for harvesting in a static growing system for cut-roses. The generic model structure was not altered. The crop production system with crop handling processes remained a stochastic discrete event system. When extended with specific properties and process elements for a static growing system the model results were compatible with those obtained in the mobile system. Four crop system specific extensions were necessary: 1) coordinate system and navigation in the greenhouse, 2) multiple operators active in different paths of greenhouse section, 3) parallel actions, and 4) operator decisions on product handling. The adapted model was validated for the harvest process at a 3.6 ha production site in the Netherlands. The model reproduced harvesting accurately. A seven workday validation for an average skilled harvester showed a relative root mean squared error (RRMSE) under 5% for both labour time and harvest rate. A validation on 96 days for various harvesters showed a higher RRMSE, 15.2% and 13.6% for labour time and harvest rate respectively. A parameter set representing company averaged operator performance explained the mean and standard deviation in a data set on labour time accurately. The increased RRMSE was mainly caused by the absence of model parameters for individual harvesters. The model was successfully used in scenario studies on the crop operation harvest of cut-roses. Work scenarios were simulated to examine effects of skill, equipment, and harvest management. The model indicated worker skill as an important factor. For rose yields of 0.5 and 3 harvested roses per m^2 harvest rate was 346 and 615 stems h^{-1} for average skilled harvesters, 207 and 339 stems h^{-1} for new harvesters and 407 and 767 stems h^{-1} for highly skilled harvesters. The model indicated economic feasibility for labour management and worker skill. Further, it was concluded that economic effects of trolley choice are small (0-2 € per 1000 stems). Working with electric trolleys is slightly more time effective, but costs were higher as a result of higher investment costs. It was not economically feasible to use electric trolleys. Also, a second harvest cycle per day was only feasible if yield quality effects would compensate for the 0.2-1.1 euro cent extra costs per harvested rose. Overall, the generic model concept performed well for a static growing system when extended with system specific properties and process elements.

Chapter 4 focussed on sensitivity analysis and uncertainty analysis of harvesting roses in a static system. The objective was to identify parameters with strong influence on labour performance as well as the effect of uncertainty in input parameters on key performance indicators. Differential sensitivity was analysed and results were tested for model linearity and superposability and verified using the robust Monte Carlo analysis method since in literature, performance and applicability of differential sensitivity analysis is questioned for models with internal stochastic behaviour. The model was not extremely sensitive for any of the 22 tested input parameters and individual sensitivities change with crop yield. Greenhouse section length and width, single rose cut time, and yield influenced labour performance most, but greenhouse section dimensions and yield also affected directly the number of harvested stems. Throughput, i.e. harvested stems per second, being the preferred metric for labour performance, was most affected by single rose cut time, yield, number of harvest cycles per day, greenhouse length and operator transport velocity. The model is insensitive for σ of lognormal distributed stochastic variables describing the duration of low frequent operations in the harvest process, like loading and unloading rose nets. In uncertainty analysis the coefficient of variation for the most important outputs labour time and throughput is around 5%. The main sources of model uncertainty were in parallel execution of actions and trolley speed. As a result, the coefficient of variation and the 99% uncertainty range is relatively large for accumulated transport time and overlap time. The uncertainty effect of these parameters in labour time, throughput and utilisation of the operator is acceptably small with CV < 5%. Total sensitivity as determined using differential sensitivity analysis and Monte Carlo analysis essentially agreed. The combination of both methods gave full insight in both individual and total sensitivity of key performance indicators.

In *Chapter 5*, the objective ‘model based improvement of the operation of horticultural production systems’ had focus. This objective was narrowed down to ranking simulated labour management scenarios in a cut-rose greenhouse. Eight scenarios with worker skill as a central theme were simulated including a practical labour management scenario applied by a Dutch cut-rose grower company. The crop operations harvest, disbudding and bending were considered, which represent over 90% of crop-bound labour time. The GWorkS-model was prepared for simulation of disbudding and bending in addition to harvest, as well as for full scale simulation of the greenhouse using available or assigned workers and equipment. The sub-models on disbudding and bending were verified using data acquired in practice. Both processes were reproduced accurately. The integrated scenario study on harvest, disbudding and bending showed differences between scenarios of up to 5 s per harvested rose in simulated labour time and up to 7.1 € m^{-2} per year in labour costs. The simulated practice of the grower and the simulated minimum cost scenario indicated possible savings for a grower of 4 € m^{-2} per year, that is 15% of the labour cost total for harvest, disbudding and bending and close to 150 k€ per year for the studied greenhouse. Scenarios pointed out that working with low skilled, low paid workers is not effective. Specialised workers were most time effective, -17.5% compared to the reference, but overall a permanent team of skilled generalists ranked best in a multi-factorial assessment. Reduced crop operation diversity per day improved labour organisational outputs but ranked almost indifferent. The reference scenario was outranked by 5 scenarios. In *Chapter 5*, the GWorkS-model provided clear answers to research questions concerning operations management and labour organisation, using the full complexity of crop operations and a multi-factorial criterion. Thus, model-based improvement of crop operations is a real option in preparation of new management strategies.

Overall, this study demonstrated that greenhouse crop operations may be characterised as a discrete event system in which operator actions are identifiable as a chain of events. Discrete event simulation, as implemented in the GWorkS model, described greenhouse crop operations mechanistically correct and predicts labour use accurately. This first generation model-based method was developed and validated by means of data acquired at commercial growers. All underlying sub-models on harvest, disbudding and bending were verified. The model-based assessment of scenarios was demonstrated for harvest of cut-roses in a greenhouse section (*Chapter 3*) and for three crop operations, harvest, disbudding and bending in a full scale greenhouse (*Chapter 5*). It may therefore be concluded that the objective of the research was realised. To the best of our knowledge, the GWorkS-model is the first model that is able to simulate the crop operations in a greenhouse in one simulation taking into account the available resources and staff. The model potentially supports growers and designers in analysis and evaluation of design concepts for system innovation. Contributions to interpretability, manageability and traceability of effects of labour organisation changes were shown in *Chapter 5*. Feasibility evaluation and multi-factorial assessment by simulation is a good option to test and evaluate changes in work methods. The future success of this model based method depends on its embedding in operational

research in greenhouse horticulture and its application in the development of greenhouse production system innovations.

Samenvatting

In de Nederlandse glastuinbouw vertegenwoordigt arbeid 25-30% van de productiekosten en is daarmee een belangrijke kostenfactor. Om concurrerend te blijven op de (inter) nationale markt, zal verbetering van de arbeidsefficiëntie in de tuinbouw de komende decennia onverminderd belangrijk blijven. Besluitvorming ter verbetering van de arbeidsefficiëntie is niet eenvoudig. Welke technologie is effectief en is daarvoor wijziging van het productiesysteem en de werkmethoden nodig? Voor een goede concurrentiepositie vereisen telers investeringszekerheid, lagere productiekosten, een verbeterd productie-niveau, en een gehandhaafde of verbeterde productkwaliteit. Realisatie van lagere arbeidskosten in gewashandelingen middels technische innovatie en een verbeterd arbeidsmanagement is een van de uitdagingen. Door de complexe gewasomgeving vervaagt de analogie met de industrie. Het faalrisico van investeringen voor telers kan worden verkleind door voorstellen voor systeemaanpassing te onderwerpen aan een kwantitatieve evaluatie voorafgaand aan implementatie in de praktijk. Kwantitatieve modellen zijn nog niet eerder ingezet voor een effectieve systeemanalyse en inbedding van nieuwe technologie of werkmethoden in gewashandelingen.

Dit onderzoek had als doel een modelgebaseerde methode te ontwikkelen ten einde arbeid in gewasproductiesystemen te analyseren en effecten van veranderingen in het systeem te kwantificeren, om zo een bijdrage te leveren aan een effectieve glastuinbouw met een efficiënt gebruik van arbeid en technologie. Dit kan de slagingskans van systeeminnovaties verhogen en beslissingsondersteuning bieden in arbeidsmanagement. Binnen dit project werd de eerste versie van deze modelgebaseerde methode ontworpen en geïmplementeerd. Het model kreeg de naam GWorkS, een acroniem voor Greenhouse Work Simulation. Simulatie en modelbouw resulteerde in een kwantitatief begrip van arbeid in gewashandelingen. De methode maakt simulatie van bestaande productiesystemen, analyse van verbeteringen, en identificatie van knelpunten in operationele processen mogelijk. Beoogde oplossingen kunnen kwantitatief geëvalueerd worden zonder ze eerst te realiseren. Evaluatie van arbeid in gewashandelingen op basis van simulatie is relatief nieuw in de glastuinbouw. Omdat modelmatige evaluatie van productiesystemen in de industrie meer geaccepteerd is, diende de industrie als inspiratiebron voor dit onderzoek.

Het onderzoek werd afgebakend tot de teelt van grootbloemige snijrozen, een gewas dat representatief is voor veel snijbloemen en vruchtgroenten. *Hoofdstuk 2* presenteert het model voor discrete-event-simulatie van arbeidsprocessen in een kas met een mobiel teeltsysteem voor rozen. Dit mobiele teeltsysteem werd ontworpen om de arbeidsefficiëntie te verhogen. Er bleven echter vragen over instellingen van operationele parameters voor de beste prestaties. De focus in dit hoofdstuk lag op simulatie van de handelingen van één of

twee oogsters die op één locatie op het hoofdpad werken aan een bewegende goot van een automatisch roulerend teeltgootsystem. Effecten van systeemwijzigingen werden kwantitatief zichtbaar gemaakt door simulatie. Bij een teler met een modern mobiel teeltsysteem werd data verzameld en ingezet om het GWorkS-model te testen en te valideren. De gesimuleerde systeemprestaties werden vergeleken met de gemeten prestaties. Het model schatte de arbeidstijd voor oogst met een nauwkeurigheid van 94%. Een validatie van een maand resulteerde in een nauwkeurigheid van 92% en een relatieve gemiddelde kwadratische fout (RRMSE - relative root mean square error) van 18%. De waarde van RRMSE werd veroorzaakt door ontbrekende data, zoals het aantal werknemers werkzaam aan de bewegende goot en de werkelijke gootsnelheid. Het resultaat toonde effecten van interne parameters, zoals de actuele snelheid van de oogster en van de goot bij verschillende opbrengstniveaus. De structuur en opzet van het GWorkS-model is generiek waar mogelijk en systeem-specifiek waar onvermijdelijk. Deze aanpak versterkt de flexibiliteit van het model en de toepasbaarheid daarvan in andere teeltsystemen. Het model kon worden gebruikt voor zowel het ontwerp als het operationele management van dit type productiesysteem.

De generieke aanpak van het voorgestelde modelconcept werd getest in *hoofdstuk 3* door migratie van het oogstproces van snijrozen in een mobiel teeltsysteem naar oogst in een statisch teeltsysteem. De flexibiliteit en de overdraagbaarheid van het modelconcept werd bewezen en gevalideerd voor de oogst van snijrozen in een kassectie bestaande uit 12 teeltpaden waar per dag één of twee maal werd geoogst. De modelstructuur werd uitgebreid met eigenschappen en proces-elementen van het statische teeltsysteem: 1) coördinatenstelsel teeltsysteem en navigatie, 2) gelijktijdige activiteit van oogsters in verschillende paden, 3) parallelle uitvoering van handelingen, en 4) een beslissingsboom voor productverwerking op de teeltvloer. Het aangepaste model werd gevalideerd met data afkomstig van een 3,6 ha productielocatie in Nederland. Het model reproduceerde de arbeidsbehoefte van het oogstproces nauwkeurig. Een validatie voor zeven werkdagen en één oogster met bedrijfsgemiddelde prestatie leverde een RRMSE van onder 5% voor zowel de arbeidstijd als de oogstsnelheid. Een validatie over een tijdsperiode van 96 dagen voor diverse oogsters toonde een hogere RRMSE, 15,2% en 13,6% voor respectievelijk arbeidstijd en oogstsnelheid. Een parameterset van de gemiddelde bedrijfsprestatie voor oogst verklaarde zowel het gemiddelde als de standaarddeviatie van de gemeten arbeidstijd in een dataset nauwkeurig. De toegenomen RRMSE werd voornamelijk veroorzaakt door prestatieverschillen tussen individuele oogsters en het ontbreken van modelparameters daarvoor.

Het model werd ingezet in scenariostudies van de oogst van snijrozen. In verschillende scenario's werden effecten onderzocht van de vaardigheid van werknemers, van keuze van apparatuur en van oogstmanagement. Het oogstvaardigheid van werknemers was een belangrijke factor. Voor 0,5 en 3 geoogste rozen per m^2 bedroeg de gesimuleerde oogstcapaciteit 346 en 615 rozen per uur voor de gemiddeld presterende oogster, 207 en 339 rozen per uur voor nieuwkomers en 407 en 767 rozen per uur voor bekwame oogsters. Volgens modelberekening is het economisch haalbaar om zich in het management van arbeid te richten op maximaal vaardige medewerkers. Ook bleek het economisch effect van de elektrische oogstkarren klein te zijn, 0-2 € per 1000 rozen. Werken met elektrische oogstkarren was tijdefficiënter, maar dit werd gecompenseerd door hogere vaste kosten. Een tweede oogstcyclus per dag was alleen haalbaar als de 0,2-1,1 eurocent extra kosten per geoogste roos worden gecompenseerd door een effect in gewasopbrengst. Na implementatie van systeem-specifieke eigenschappen en proces-elementen waren de resultaten van het generieke modelconcept vergelijkbaar met behaalde resultaten in het mobiele teeltsysteem.

Hoofdstuk 4 beschrijft een gevoeligheidsanalyse en een onzekerheidsanalyse van arbeid tijdens het oogsten van rozen in een statisch teeltsysteem. Het doel was de parameters te identificeren met een grote invloed op arbeidsprestaties, evenals het effect van de onzekerheid in input-parameters op de model-output. Wegens het stochastisch karakter van het model zijn twee gevoeligheids-analysetechnieken toegepast omdat in de literatuur een voorbehoud wordt gemaakt t.a.v. de prestaties en de toepasbaarheid van differentiële gevoeligheidsanalyse voor modellen met intern stochastisch gedrag. De gevoeligheid voor enkelvoudige parameters werd geanalyseerd m.b.v. de differentiële methode en de resultaten werden getest op geldigheid door het model te testen op lineariteit en optelbaarheid. De totale gevoeligheid werd gecontroleerd met behulp van de robuuste Monte Carlo methode. Het model is niet zeer gevoelig voor de 22 geteste invoerparameters. Gevoeligheden voor individuele parameters veranderen met de gewasopbrengst. De parameters lengte en breedte van een kasafdeling, de cyclustijd voor het snijden van een enkele roos, en gewasopbrengst, d.w.z. het aantal te snijden bloemen per m^2 per dag, beïnvloeden de arbeidstijd het sterkst. De afmetingen van een kasafdeling en de gewasopbrengst beïnvloeden het aantal geoogste rozen direct. Een betere indicator voor de arbeidsprestatie, de throughput d.w.z. het aantal geoogste rozen per seconde, werd het meest beïnvloed door de cyclustijd voor het snijden van een enkele roos, de gewasopbrengst van de dag, het aantal oogstcycli per dag, kaslengte en de transportsnelheid in het pad. Het model is ongevoelig voor σ van lognormale verdeelde stochastische variabelen die de duur van laagfrequente activiteiten in het oogstproces beschrijven, zoals het lossen van bundels rozen van oogstkarren. In de onzekerheidsanalyse ligt de variatiecoëfficiënt voor de belangrijkste modeluitvoer arbeidstijd en throughput rond de 5%. De belangrijkste bronnen van onzekerheid zijn de mate van synchrone uitvoering van oogsthandelingen enerzijds en transport in het pad anderzijds. Hierdoor is de variatiecoëfficiënt en het 99% betrouwbaarheidsinterval van de onzekerheid in de geaccumuleerde transporttijd en overlaptijd relatief groot. De bijdrage van deze output aan de onzekerheid in arbeidstijd, throughput en het utilisatie van de medewerker is aanvaardbaar klein (CV <5%). De totale gevoeligheid resulterend uit de differentiële gevoeligheidsanalyse en uit de Monte Carlo analyse stemmen overeen. De combinatie van beide methoden gaf volledig inzicht in zowel de individuele gevoeligheid als de totale gevoeligheid van de belangrijkste prestatie-indicatoren.

In *hoofdstuk 5* stond de zoektocht naar verbetering van de operationele werking van tuinbouwproductiesystemen middels modelsimulatie centraal. Dit doel werd afgebakend tot het ranken van simulatieresultaten voor verschillende arbeidsmanagementscenario's. Er werden acht scenario's gesimuleerd met de vaardigheid van de werknemers als centraal thema. Een van de scenario's was een nabootsing van de arbeidspraktijk bij een Nederlandse rozenkweker. De gewashandelingen oogsten, pluizen (verwijderen zijscheuten van bloemdragende stelen) en buigen (van niet productieve stelen uit de groeiruimte van de bloemen) zijn gesimuleerd. Deze gewashandelingen vertegenwoordigen meer dan 90% van de gewas gebonden arbeidstijd. Het GWorkS-model werd uitgebreid voor 1) simulatie van pluizen en buigen naast oogsten, 2) simulatie van de volledige kas (3.6 ha) met simultane werkuitvoering door alle beschikbare dan wel toegewezen werknemers en apparatuur. De deelmodellen voor pluizen en buigen werden geverifieerd met behulp van gegevens verkregen in de praktijk. Beide processen werden nauwkeurig gereproduceerd. De geïntegreerde scenariostudie over de oogst, pluizen en buigen toonde, tussen de scenario's, verschillen in gesimuleerde arbeidstijd voor alle bewerkingen tezamen van maximaal 5 s per gesneden roos en verschillen in arbeidskosten tot 7,1 € m^{-2} per jaar. De gesimuleerde praktijk van de teler en het gesimuleerde scenario met minimale kosten wijzen op een mogelijke arbeidsbesparing voor de teler van € 4 m^{-2} per jaar. Dat is 15% van de totale arbeidskosten voor de oogst, pluizen en buigen en dicht bij 150 k€ per jaar voor de onderzochte kas. Het werken met laaggeschoolde, laagbetaalde werknemers is volgens de scenario studie niet effectief. Gespecialiseerde arbeiders waren het meest tijdeffectief ten opzichte van de referentie, met 17,5% minder arbeidstijd. In een multifactoriële evaluatie werd een vast team van ervaren generalisten als beste gerangschikt. Een vermindering van het aantal gewashandelingen per dag van 3 naar 2 verbeterde de tijdigheid van taakuitvoering, maar vertoonde geen duidelijke rangordeverbetering ten opzichte van de referentie. Het referentiescenario werd overtroffen door 5 scenario's. In *hoofdstuk 5* worden middels het GWorkS-model duidelijke antwoorden gevonden op vragen met betrekking tot operations management en arbeidsorganisatie, op basis van integrale simulatie van gewashandelingen en een multifactorieel criterium. Modelgebaseerde verbetering van de uitvoering van gewashandelingen lijkt hiermee een reële optie in de voorbereiding van nieuwe arbeidsmanagementstrategieën.

Concluderend kan gesteld worden dat gewashandelingen gekarakteriseerd kunnen worden als een discrete-event-systeem waarin acties van de operator kunnen worden beschouwd als een keten van gebeurtenissen. Discrete-event-simulatie, zoals geïmplementeerd in het GWorkS-model, beschrijft gewashandelingen in kassen op mechanistisch correcte wijze en voorspelt de benutting van arbeid nauwkeurig. Deze eerste modelgebaseerde methode werd ontwikkeld en gevalideerd aan de hand van gegevens verkregen bij commerciële telers. Alle deelmodellen van de gewashandelingen oogst, pluizen en buigen werden geverifieerd. Een modelgebaseerde evaluatie van scenario's werd getoond voor de oogst van de snijrozen in een kassectie (*hoofdstuk 3*) en voor geïntegreerde planning en uitvoering van drie gewashandelingen, oogsten, pluizen en buigen in een volledige kas (*hoofdstuk 5*). Derhalve kan worden geconcludeerd dat de doelstelling van het onderzoek werd gerealiseerd. Volgens de onderzoekers is GWorkS het eerste model dat in staat is in één model-run alle gedefinieerde gewashandelingen te simuleren, rekening houdende met beschikbaar personeel en personele vaardigheden als ook beschikbare productiemiddelen. Het model kan telers en ontwerpers ondersteunen in de analyse en evaluatie van ontwerpconcepten voor systeeminnovatie. Haalbaarheidsevaluatie en multifactoriële beoordeling door middel van simulatie is een goede methode voor beoordeling van veranderingen in werkmethoden. Model bijdragen aan interpretatie, beheersbaarheid en de traceerbaarheid van effecten van veranderingen in de arbeidsorganisatie werden getoond in *hoofdstuk 5*. Het toekomstig succes van deze modelgebaseerde methode hangt af van de inbedding in operationeel onderzoek in de glastuinbouw en van de toepassing ervan tijdens de ontwikkeling van innovaties van kasproductiesystemen.

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This PhD-thesis reflects results of research conducted in a time period of 5 years. During these years many people contributed to the work and the discussions on the subject. I would like to express my gratitude to all who supported me. Finally I would like to thank PE&RC for all support and training, and in my case for accepting some ‘old stuff’. I enjoyed the PE&RC staff attitude, seeking both scientific quality and a human touch in their approach to PhD-candidates.

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Wageningen, March 2015

About the Author

Albertus (Bert) van ’t Ooster was born on August 5, 1960 in Voorthuizen, the Netherlands, on a farm with at that time an integrated production of livestock and arable crops. After receiving his degree of pre-university education (VWO) in 1978 at CSE, Ede, he received his MSc degree in Agricultural Engineering in 1984 at Wageningen University (*cum laude*). During his study he completed four MSc-thesis subjects in agricultural engineering, applied physics, systems and control and agricultural economics and an internship at the Federal Agricultural Research Centre (FAL) in Braunschweig, Germany. The main thesis subject was dynamic modelling of the greenhouse climate, a contribution to the PhD-thesis ‘Greenhouse climate: from physical processes to a dynamic model’ by Gerard Bot. During his study he also contributed to the PhD-thesis ‘Optimal cereal combine harvester operation by means of automatic machine and threshing speed control’ by Wim Huisman.

Since 1984, he is assistant professor at the Farm Technology Group of Wageningen University. He was always involved in courses in the field of Agricultural Engineering and gave supervision to over 100 MSc-Thesis projects. Currently he teaches Greenhouse Technology, Biosystems Design, Building Physics and Climate Engineering. His main interests are data and systems analysis, systems operations, continuous time and discrete event modelling, and integral systems design. The main application fields are biosystems design, on-farm operations, transport physics of indoor climate, climate engineering, sustainable energy, and emissions in crop and animal production. He is experienced in experimental and model based research. Research focuses were measuring and modelling natural ventilation rates and ammonia emission from dairy cow houses, simulation of postharvest conservation using finite elements, solar heat load on shaded buildings, passive and active solar energy use, integrated design of animal housing, forced ventilation systems, and energy use in animal houses. For educational and research purposes, he developed several simulation models. Some examples are 1) GTa-tools - the greenhouse technology application tools, 2) Glassim-ATU - air treatment units in a dynamic greenhouse climate model, 2) Enbeg - energy use in broiler houses, 3) SunShade - solar radiation on shaded building envelopes, 4) ClimSim - dynamic model for indoor climate simulation and optimal control of the climate in naturally ventilated dairy cow houses, 5) PLUS - Psychrometric lookup system.

From April 2009, he was partly employed at Wageningen UR greenhouse horticulture to conduct his PhD research on model-based evaluation of operational processes in horticultural production systems with high human labour input. The research was a cooperation between Wageningen UR greenhouse horticulture and Wageningen University, Farm Technology group. This thesis is the outcome of this research.

He was (co-)author of more than 50 publications in peer refereed journals, conference proceedings, books, lecture books and professional magazines. Bert is member of (inter)national professional organizations: ISHS, EurAgEng, NVTL, KLV. You can contact him at: Bert.vantOoster@wur.nl

List of publications

Refereed articles in a scientific journal

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PE&RC Training and Education Statement

With the training and education activities listed below the PhD candidate has complied with the requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review of literature (6 ECTS)

- Review on methods for analysis, modelling and optimisation of automated production processes in greenhouse horticulture using analogies in industry

Writing of project proposal (4.5 ECTS)

- Systematic design of automated sustainable horticultural production systems

Post-graduate courses (3 ECTS)

- Building physics finite element package for modelling temperature behaviour of buildings; Civil Engineering, TU-Delft (1988)
- Uncertainty modelling and analysis (2013)

Laboratory training and working visits (4 ECTS)

- Working visits on natural ventilation and animal welfare; Guelph University, Univ of Saskatchewan, Urbana Champaign, Univ. of Illinois, Cornell University (1988)

Invited review of (unpublished) journal manuscript (2 ECTS)

- Journal of the Air & Waste Management: ammonia emission process affected by ventilation airflow, pen partition and location of emission surface in a model pig house, research paper (2010)
- Biosystems Engineering: efficiency of carbon dioxide enrichment in an unventilated greenhouse, full length article manuscript (2012)

Competence strengthening / skills courses (2 ECTS)

- Professional in supervision, PS (2012)
- Mobilising your – scientific – network, MSN (2014)

PE&RC Annual meetings, seminars and the PE&RC weekend (1.2 ECTS)

- PE&RC Weekend (2012)
- PE&RC Mini symposium foliar traits and photosynthetic characteristics (2014)

Discussion groups / local seminars / other scientific meetings (6 ECTS)

- Interdisciplinary working groups with the mission to write: Climate standards for pigs; measuring climate in pig housing systems; methods for measuring ammonia emission from livestock buildings (1989-1994)
- Modelling and statistics network, MSN (2012, 2013)

International symposia, workshops and conferences (7 ECTS)

- CIGR XII/AgEng; 3 papers; Milano, Italy (1994)
- International horticultural congress; 2 papers; Lisbon (2010)
- International symposium on high technology for greenhouse system management;4 papers; Naples, Italy (2007)

Lecturing / supervision of practical's / tutorials (3 ECTS)

- Coordination and teaching MSc-course greenhouse technology (2009-2014)
- Coordination and teaching BSc-course building physics and climate engineering (2009-2014)
- Coordination and teaching MSc-course biosystems design (2010-2014)

Supervision of 8 MSc students

- Analysis of workflows in crop operations at modern truss tomato growers (2 students)
- Analysis of crop handling processes in conventional and mobile rose production systems (3 students)
- Data analysis and simulation of harvest in sweet pepper (2 students)
- Modelling temperature stress in tomato to find feasible climate management improvements in Greek greenhouses (1 student)

Colophon

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