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Research Paper

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

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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 the literature, performance and applicability of differential sensitivity analysis has been 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 into both individual and total sensitivity of key performance indicators.

1. 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

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Nomenclature

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 variable's 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 variable's natural logarithm for $LN(\mu, \sigma^2)$ or the variable itself for $N(\mu, \sigma^2)$
SD	Standard deviation (data set)
$S_{i,j}$	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 (–)

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, in press), 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 of 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 aims of this study were 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 model's 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 values (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