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Control of Production-Inventory systems of perennial crop seeds

Robbert van der Kruk [a,*], René van de Molengraft [a], Herman Bruyninckx [a,b], Eldert J. van Henten [c]

[a] Eindhoven University of technology, Mechanical Engineering, The Netherlands
[b] KU Leuven, Mechanical Engineering, Leuven, Postbus 2420 3001, Belgium
[c] Wageningen University & Research, Farm Technology Group, Wageningen, P.O. Box 16, 6700AH, The Netherlands

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ABSTRACT

Production planning and inventory control are essential for the logistic performance of breeding companies. In this paper, we discuss such a system for perennial crop seeds in which production during multiple years and a number of growth cycles before production starts are characteristic. Large variations in yield and demand are typical and could easily lead to shortages or excess in seed stock. Both are costly phenomena. For these reasons, production planning as currently done by seed breeders without much technical support is extremely challenging. This paper describes and models the seed production process of a breeding company and examines its impact on inventory levels. The approach involves developing a time-discrete model parameterised with historical data. Subsequently, three control schemes are formulated: a classical feedback–feedforward PID controller, a feedback–feedforward PID controller with a Smith Predictor and a Model Predictive Control scheme.

The goal of this paper is to present and validate a novel seed production–inventory model. Only aged plants are destroyed after a fixed number of production cycles. The ordering of new plants is the input control variable. The model represents the multi-year seed production of perennial crop seeds and expands upon the dead-time delay model, which typically does not account for production level uncertainty in production–inventory systems. The parameters of the model create a general approach; for both annual and perennial crop seeds.

1. Introduction

Each spring, farmers decide how to allocate their free land for possible crops. After deciding which area of land to plant, they buy seeds or seedlings. Perennial crops such as artichoke, asparagus, rhubarb, and strawberry are crops that, unlike annual crops, do not need to be seeded or planted each year and are productive for multiple years. In plant breeding, using modern genetic methods, hybrid varieties of perennial crops are bred that have a high yield, are resistant to diseases and pests, and have other desired properties. The seed production for hybrid varieties itself typically takes place in a closed environment such as a greenhouse. Due to their perennial nature, the number of plants used for seed production largely determines the yield of seeds for a multitude of years. Some crops provide the first seed yield in the second season. Farmers' planting decisions may be heavily influenced by their experience during the previous growing season, causing large ordering fluctuations; especially with perennials, they could decide not to order and use their excising ageing plants another period to harvest from. Experience shows that variations of approximately 30 to 35% above and below the average values for random variables should be considered [1]. Due to significant fluctuations in both yield and demand, seed companies find it necessary to depend on their stocks of seeds harvested preceding growing seasons to ensure timely delivery to farmers. So the inventories are used to regulate the imbalances in the normal sequence of activities in production and sales processes to create a stabilising effect on material flow patterns. Fig. 1 illustrates authentic data on the seed stock levels of an asparagus variety to illustrate the extremely difficult task of planning to ensure seed deliveries at all times. The blue line represents the actual seed level until 2018 and the actual plan from 2019 onwards. The red lines denote the upper and lower stock levels required to ensure adequate supply. Shortages were experienced in the years 2010–2012, while a remarkably elevated inventory level persisted from the year 2018 onwards. In that year, the decision was made to uproot part of the seed production plants. Evidently, the inventory system failed to adhere to the prescribed limits, resulting in both elevated costs and difficulties in fulfilling deliveries. This situation is not uncommon for seed breeders.

A common way of working is to plant for the highest demand level given the lowest yield level and to discard excess seeds and plants in case stock levels become too high.

Fig. 2 shows the planning cycle to control seed stock. Throughout the year, the demand forecast and the actual inventory level are used

* Corresponding author.
E-mail address: r.j.v.d.kruk@tue.nl (R. van der Kruk).

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Nomenclature

$\hat{d}$	Demand forecast [seeds/year]
$\hat{I}$	Estimated inventory level [seeds]
a	Planting area for seedlings [m^2]
a_{fd}	Planting area for seedlings originated from demand forecast feedforward [m^2]
a_{fi}	Planting area for seedlings originated from reference feedforward [m^2]
b_n	Standard yield coefficient of plants in n years after planting [seeds/m^2]
I	Inventory level [seeds]
n	Period number [year]
L	Stock level expressed in years to meet the demand forecast the first L periods
M	First year to harvest [year]
N	Number of years seeds are harvested from a plant [year]
k	Period number [year]
N_p	Prediction horizon [year]
N_u	Control horizon [year]
P	Nominal Production [seeds/year]
p	Standard production [seeds/m^2]
r	Rejects [seeds/year]
Y	Total volume available for harvest [seeds/year]
z	Forward shift operator
z^{-1}	Backward shift operator

to define the seedling planting area, which will contribute to seed production several harvest cycles later. The planting area is directly related to the number of plants. To check the level of inventory, the seeds in the warehouse are counted annually. The production process is characterised by a time delay of several periods to create the first seeds. These plants are utilised over multiple years for harvesting until their yield diminishes. Unpredictable variations in sales and yield during multiple years of production pose a challenge to breeders, making it extremely difficult to accurately manage seed inventory levels.

1.1. Literature review

The literature on production–inventory systems with stochastic demand is extensive and still ongoing [2–4]. In the following, we focus on research in the single-product setting with a demand forecast that shares relevant features with our problem. We start with agri-food products, then discuss papers with systems using a feedback method to cope with production variations.

The literature on production–inventory systems in agriculture is scattered [5], and there is no discussion of perennial crop seeds. Forecasting the demand for optimal stock control with a long lead time was described in general by Kaplan [6]. In [7], an operations research method for an inventory model for food service with independent Gaussian distributed demands was described to optimise contribution margins. Their continuous-time inventory model included deterioration. However, supply dynamics was neglected, lead time was considered zero, and yield was assumed to be constant. The perishable inventory for fresh fruits has been intensively studied, and numerous models have been proposed in the literature for the various situations that exist [8–10]. These models do not include variations in production (yield) and multi-period production. Often used classical $M/M/1/\inf$ queueing inventory systems typically do not use information from the inventory level for feedback to a control system [4]. Fig. 3 shows the same production–inventory system presented in two different frameworks, namely operational research (OR) and control theory. The same elements of the system are understood in different ways in each domain. The OR problem of finding optimal order quantities to maintain an appropriate inventory level taking into account lead time and varying demand turns to the following formulation: design a controller; find an optimal system input to maintain an appropriate system output with consideration of system time delay and varying disturbance [11].

Control theory was applied in production–inventory systems to reduce inventory variation and reduce demand amplification; see Simon [12] and Ortega et al. [13]. Feedback was used for inventory deficiencies that led to deterioration and rejection. Production–inventory systems have been modelled using both continuous-time and discrete-time based on the way that inventory status is reviewed. Its three main components are the forecasting mechanism, the production–inventory process, and the controller strategy; see Disney et al. [14]. Ignaciuk [15] reports the case of production–inventory control with unknown variable demand, deterioration of stock over time, and constant supply delay using a Smith Predictor time discrete control method. The bullwhip effect and dead-time compensation were successfully counteracted. However, multi-period production dynamics are not addressed. The environmental effects during seed production are complex, involving overlapping gene networks active independently in fruit, seed coat, and zygotic tissues, resulting in yield variations [16] to support the conclusion that the variation in the production yield cannot be ignored. Tosetti et al. [17] presented an automatic pipeline feedback order-based production control system with PID and demand forecast control for production–inventory systems. It uses a Work In Progress (WIP) pipeline for feedback. However, WIP is a result of planning and is a feedforward method by nature. Multi-period production or reproduction dynamics were not addressed by the production model of a dead-time.

[18] use an Order-Up-to (OUT) dead-time model obtained using a state-space approach and conclude that a single feedback loop PID control ordering outperforms proportional controllers with two feedback loops in reducing the bullwhip effect and regulating the inventory level. Constraints of states and ordering were not addressed. The application of Model Predictive Control and systematically designed control action in the replenishment systems is still not very common, and not many researchers have devoted their work to this matter. Therefore, there is still sufficient room for future improvements [19]. It was concluded in [5] that too little is done in developing an integrated approach to model harvesting and processing in agri-chains. To mitigate yield variation and demand uncertainties, a second growing cycle can be used in another hemisphere, as reported for the production and inventory of seed corn [20]. Modelling of the production of agricultural vegetables or fruits, such as tomatoes, is not uncommon and was recently reported by [21,22]. Advanced control methods in greenhouses have been reported by [23] and [24].

1.2. Main contribution and organisation of this paper

The main contribution of this paper lies in presenting a planning method that effectively balances inventory levels and anticipates future seed deliveries. The study demonstrates that integrated production and inventory planning for perennial crop seeds can be significantly improved through the use of semi-automatic MPC control, facilitated by a straightforward tool and an understandable methodology. This paper is organised as follows. In Section 2, the production of seeds is described and modelled. The control methods are presented in Section 3. In Section 4, the results are given and discussed in Section 5. Finally, in Section 6, the conclusion follows.

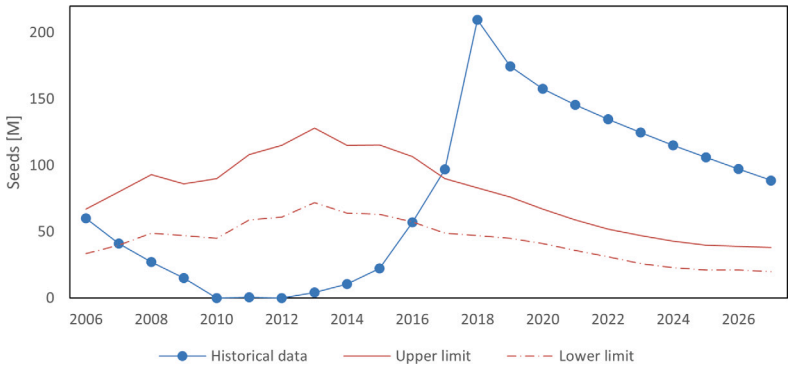


Fig. 1. The actual stock levels of the Asparagus variety K89 depict instances of both insufficient and surplus inventory. The blue line represents the actual stock level, while the red lines mark the upper limit (six years of the demand forecast) and lower limit (three years of the demand forecast).

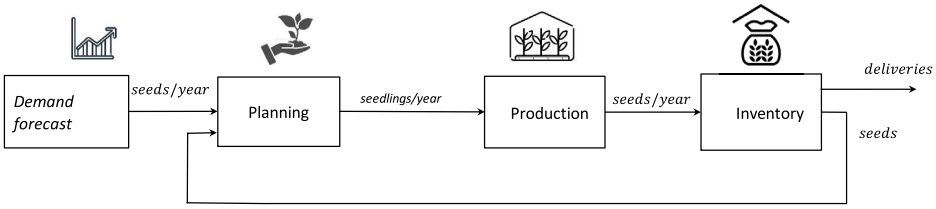
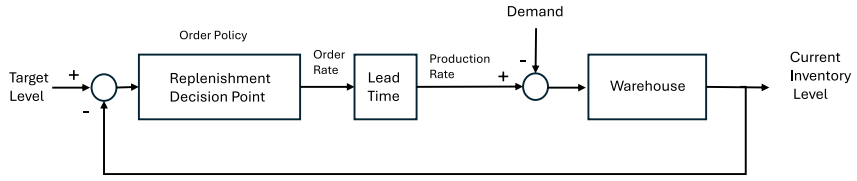
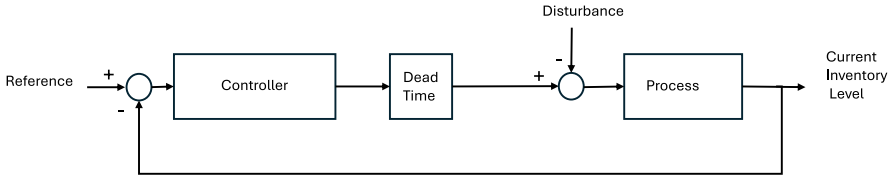


Fig. 2. Inventory control system.



(a) Operations Research Theory



(b) Control Systems Theory

Fig. 3. Production-Inventory Control Frameworks.

2. Materials and methods

It typically takes two to three years to grow hybrid seeds from new mother plants bred from seedlings of parental lines from basis seed and clones. Nursery seedlings are generated during the initial season and in greenhouses these seedlings are transplanted during the subsequent season to initiate the first production. This cycle is repeated for several years until mature plants begin to decrease their yield. The berries gathered are processed to obtain high quality coated seeds, which are then stored in the warehouse. The packaging and distribution of seeds from the inventory follow the first-in, first-out principle. The maximum storage duration before deterioration sets in is, for example, up to ten years.

2.1. Perennial seed production model

We use the information collected on the past and present resource conditions to make predictions of the future nominal production and yield. Since the growing conditions (water, crop management, temperature, humidity, number of bees) in the greenhouse areas used are similar for the varieties, we model the average yield as a function of the number of ageing years. Fig. 5 shows the average seed productivity over time for four asparagus varieties. The total volume available for harvest at a given time, the annual seed yield $Y(k)$, of the plants offers valuable data to model production. In the nursery, the yield is typically negligible, and during the first year in the greenhouse, it remains quite low. The first year to harvest (M) is equal to three years in this case. After a period of several years, the yield drops and the ageing plants

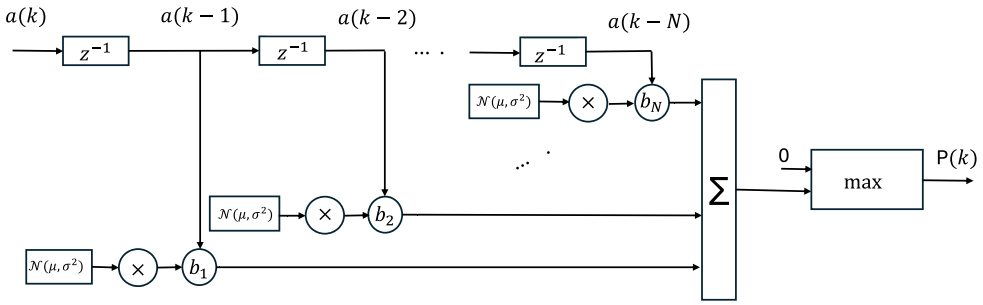


Fig. 4. Production model for perennial crop seeds. A Finite Impulse Response structure for multiple-year production of P(k) with variability in the parameters following a Gaussian distribution process. The model input is the planting area a_k.

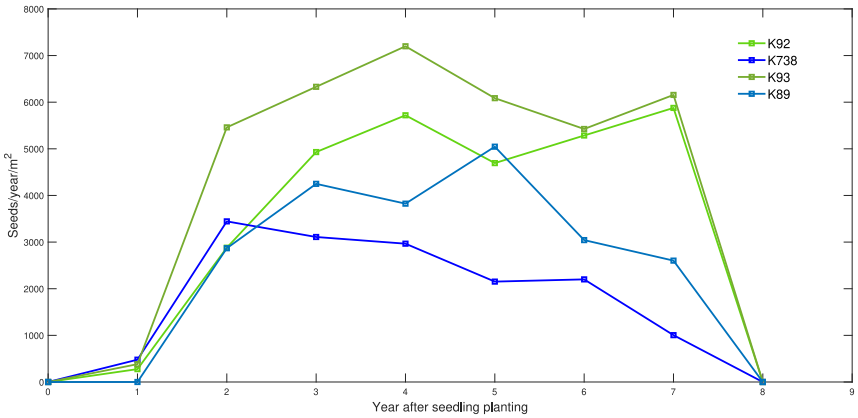


Fig. 5. Standardised production data for four varieties. Time discrete impulse response model of seed production, depicting the perennial age (N) of seven years.

are grubbed. This perennial age is named N and is seven years in this example. Fig. 4 shows the scheme of the perennial production model. The planting area $a(k)$ is the input of the model that results in seed production $P(k)$, which is a non-negative number. The model parameters $b_1 \cdots b_N$ are the product of nominal values and the Gaussian stochastic process $\mathcal{N}(\mu, \sigma^2)$. The nominal values are obtained from the annual yield data by crop specialists. Usually, these are median values for the last 10 years. This production model 4 includes a large stochastic variability of the production for all perennial years. The linear part of the model describes the nominal production for each perennial year. The linearity is related to the planting area and hence number of plants. In a greenhouse environment this proportionality is most likely as the plant distances are equally divided by the planting of the seedlings. A nonlinear model relation could occur due to the edges of the planting area where some plants have more space. These small model deviations are neglected compared to the large variability. The stochastic part of the model includes an offset, a mean percentage value. The model parameters are not constant. The model mismatch caused by these offsets and by stochastic mismatches (sigma) is validated by Monte Carlo simulations in the results section. The predictive capability of this model 4 was based on historical data of 10 years and is updated every year. A model validation study by ensuring the accuracy and quality of data was not carried out due the limited period of 10 sample moments (years). The quality of the yield data was double checked with accurate weighting equipment.

The total yield of seed production per square meter p in the year k, is modelled using the unit delay operator z^{-1}:

$$p(z) = b_1 z^{-1} + b_2 z^{-2} \cdots + b_N z^{-N} = \sum_{n=1}^{N} b_n z^{-n} \tag{1}$$

and exhibits the structure of a finite impulse response (FIR). The production $P(z)$ as a result of the planted area a becomes the product:

$$P(z) = p(z)a(z) \tag{2}$$

2.2. Inventory model

The scheme for the inventory access is demonstrated in Fig. 6 The inventory level $I(k)$, in the year k, is the sum the inventory level of the previous year and the net production $P(k-1)$ minus the deliveries $d(k)$. We assume that the quality of the seeds in the inventory does not decay before their expiration period [9].

$$I(k) = I(k-1) - d(k) + P(k-1), \quad \forall k \in \mathbb{N} \quad I(k) \geq 0 \tag{3}$$

and modelled in closed form:

$$I(z) = \frac{P(z)}{z-1} - d(z) \qquad \geq 0 \tag{4}$$

The demand forecast $\hat{d}$, in the year k, is the prediction of the demands described as

$$\hat{d}(k+i|k) \qquad \forall i \quad i = 1 \ldots N + M \tag{5}$$

The number of years to forecast equals the number of years N the plants produce seeds plus the number of years M needed for first yield.

The parameters of the model (M,N) create a general approach; for annuals: $N = 1$ and perennials: $N > 1$.

2.3. Control methods

Controlling a process characterised by time delay, finite impulse response, and notable variations is extremely difficult. These challenges escalate when data scarcity hampers model construction. A model-based approach is needed for a feedback method which anticipates the time delays and a feedforward or look-ahead method is needed using the demand forecast. An explicit yearly forecast of the deliveries is assumed to be in place for a period covering the perennial period and the time to the first harvest. These forecasts are typically used for seed production planning. A feedforward–feedback approach employing an enhanced Smith Predictor [25] for systems with time delays is

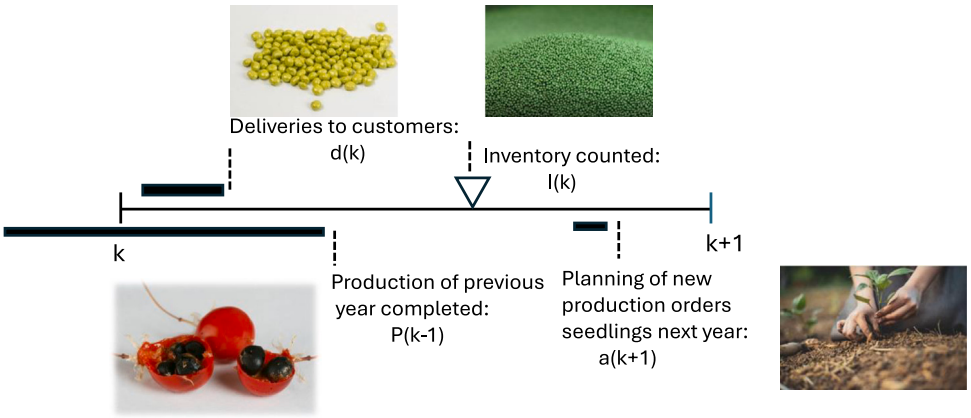


Fig. 6. Yearly events of seed stock handling. Deliveries to customers d(k), Production completion of previous season P(k−1), Inventory counting I(k) and planning of seedlings for next season a(k+1).

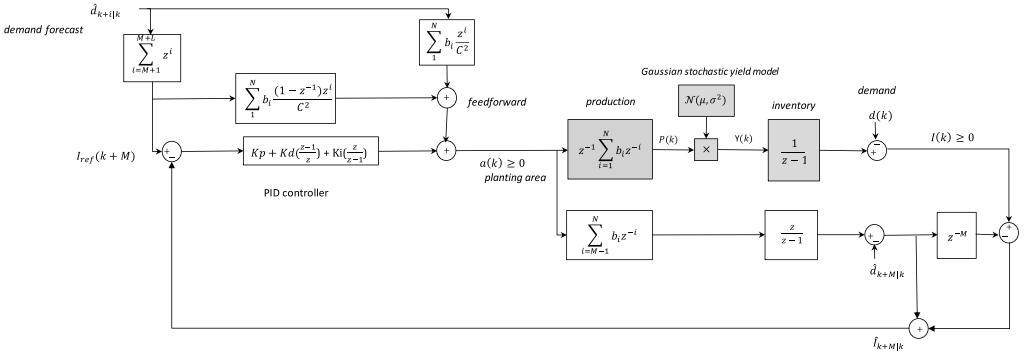


Fig. 7. SP PID control scheme. Including Smith predictor, reference and demand forecast feedforward, PID controller and models for production and inventory.

described by [26] and by [27] for a Smith predictor-based feedforward controller for measurable disturbances. In this paper, we will compare these Smith predictor-based methods with a state-of-the-art model-based approach that uses a receding horizon: Model Predictive Control (MPC).

Controlling the inventory level to the desired value $I(k)$ is done yearly compared to the reference $I_{ref}(k)$ to generate an error feedback signal as input to a feedback controller. This principle is used in both methods. The reference is derived from the demand forecast such that the inventory is driven to a number of years (L) of future sales. Hence, the reference level I_{ref} is the amount of seeds needed to meet the demand forecast during a period of L years:

$$I_{ref}(k) = \sum_{i=1}^{L} \hat{d}(k+i|k) \tag{6}$$

controller, The goal of inventory control is to keep the inventory level close to this reference. The value of L is included in the inventory policy to balance the cost of seed stock with the cost of non-deliveries. Since it takes M years to fill the stock initially, it makes sense to set L equal to M years. The control variable $a(k)$ is the planting area of the seedlings in the logistic systems named quantity of orders.

2.3.1. Feedback–feedforward control and PID Smith predictor

The control scheme with feedback control using a PID controller and a Smith predictor, reference, and demand forecast feedforward is demonstrated in Fig. 7. The reference signal $I_{ref}(k+M)$ is synchronised to the predicted output $\hat{I}(k+M|k)$ by

$$I_{ref}(k+M) = \sum_{i=M}^{L+M} \hat{d}(k+i|k) \tag{7}$$

The Smith Predictor aims to remove the time delay from the characteristic equation of the feedback system to avoid instability and increase the bandwidth. By feedforward of the demand forecast we attempt to anticipate the demand by the inverse of the standard production $y(z)$, however, $y^{-1}(z)$ is not stable and cannot be implemented. Instead, we used the weighted average of the demand forecast as an approximation such that the average production equals the average demand during N+1 years. Now, the plant area feedforward a_{fd} originating from the demand forecast becomes:

$$a_{fd}(k) = \sum_{i=0}^{N} \frac{b_i \hat{d}(i+k|k)}{C^2}, \qquad C = \sum b_i \tag{8}$$

Feedforward of the reference I_{ref} becomes an approximation of the change in inventory reference and initial stock values

$$a_{fi}(k) = \sum_{i=0}^{N} \frac{b_i (I_{ref}(k+i) - I_{ref}(k+i-1))}{C^2}, \qquad \forall k \quad k \geq 1 \tag{9}$$

$$a_{fi}(0) = \sum_{i=1}^{L} a_{fd}(i) \tag{10}$$

The control variable $a = a_{fb} + a_{fd} + a_{fi}$ is limited to non-negative values. The planting area is constrained to prevent grubbing of plants before they are aged.

2.3.2. Model predictive control (MPC)

A MPC scheme that employs a receding horizon approach [29], addresses the constrained optimal control problem in real-time during operation rather than in advance. The system Eqs. (1)–(3) are used to compute inventory levels based on the planner's input of planting areas. These forecasts are then contrasted with the reference derived from the actual long-term forecasts. Upon completion of the optimisation

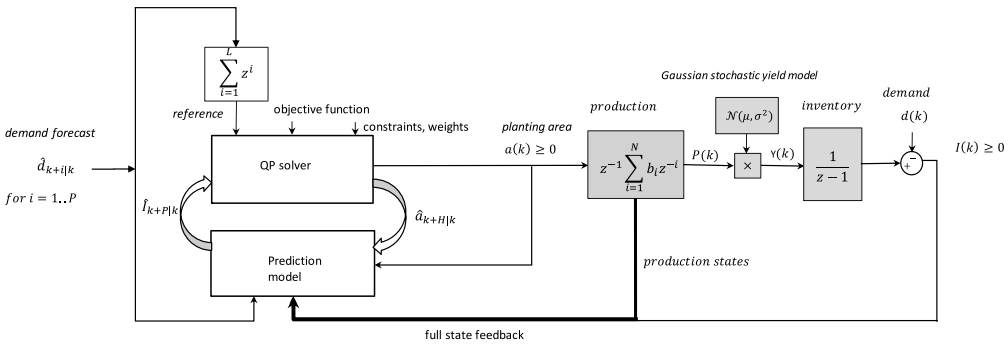


Fig. 8. Block diagram representation of the production–inventory control system using Receding Horizon (MPC) with full state feedback [28], look ahead to the forecast and reference. Models for yield and inventory (in grey). The prediction horizon is $N_p = N + M$. The control horizon is $N_u = M - 1$.

$$y(k) = \begin{bmatrix} I(k) & P_7(k) & P_6(k) & P_5(k) & P_4(k) & P_3(k) & P_2(k) & P_1(k) & P_0(k) \end{bmatrix}^T$$

Box I.

cycle, the first value of the planting area is used. The planning cycle is visualised in the control system in Fig. 8. We use a state-space representation of Eqs. (1)–(3)

$$x(k+1) = Ax(k) + Bu(k) \tag{11}$$

$$y(k) = Cx(k) \tag{12}$$

$$u(k) = \begin{bmatrix} a(k) \\ d(k) \end{bmatrix}$$

Full state feedback is obtained by the feedback of the vector (see unnumbered equation in Box I.)

The feedback includes both the output I and the production from all plant areas.

The linear state space representation of production–inventory model is:

$$A = \begin{pmatrix} 1 & b_7 & b_6 & b_5 & b_4 & b_3 & b_2 & b_1 & b_0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad B = \begin{pmatrix} 0 & -1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \end{pmatrix}$$

$$C = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & b_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & b_6 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & b_4 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & b_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & b_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & b_1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & b_0 \end{pmatrix}$$

In the B matrix the element $B(9,1)$ represents the control input (plant area a), the element $B(1,2)$ represents the unknown output disturbance (demand d). The modelled system is controllable and observable, since the observability and controllability matrix have full rank of 9. The state variable x consist of the Inventory level I and the planted areas: $x(k+1) = I(k)\ a(k-7)\ a(k-6) \cdots\ a(k)$.

For the simulations presented in this section, the planting area a is the input to the production–inventory system a which will result from an optimisation problem run by the quadratic programming solver of the MPC controller. The controller minimises the difference of the seed level and the reference over a period N_p, known as the prediction horizon. N_p has to be larger than the timescales of the relevant slow dynamics of the production–inventory system to be able to properly optimise the control inputs. This is mathematically represented by

$$\underset{a(k)}{\text{minimize}} \quad \sum_{i=1}^{N_p} (\hat{I}(k+i) - I_{ref}(k+i))^2 + \lambda \sum_{i=0}^{N_u-1} (\Delta a(k+i))^2 \tag{13a}$$

subject to

$$x(k+1) = Ax(k) + Bu(k), \tag{13b}$$

$$y(k) \quad = Cx(k), \tag{13c}$$

$$a(k) \geq 0, \quad I(k) \geq 0, \tag{13d}$$

$$x(0) = x_0 \tag{13e}$$

The scheme employs a prediction horizon Np of N+M years and a control horizon N_u of M-1 years. The prediction horizon accounts for the number of years seeds can be harvested from a plant (N) and the number of years (M) to the first harvest. The control horizon equals the number of years before the first harvest (M-1). The weighting parameter λ is used for damping to avoid sudden changes in planting areas over the years that make them less sensitive to variation in yield.

The shaping of both control methods is straightforward by aiming at comparable rise times. Fig. 9 shows the results for a reference step input, input and output step disturbance as demonstrated in the inventory, production and planting order time series. The presence of substantial variations and the extensive time-frames (spanning dozens of years) required for experiments render it impractical to conduct research solely through experimental tests. Instead, with original data on forecast, production, and sales [30], we validate the results through Monte Carlo simulations.

3. Results

The validation of the controlled (SP, PID and MPC) model of the production–inventory systems is carried out by Monte Carlo simulations for two varieties and is used to perform sensitivity analysis to study how the model responds to randomly generated disturbance inputs. It involves a three-step process []MonteCarloSimulation by: randomly generating a number of inputs according to the statistical data in Table 1 running a simulation for every input, aggregate mean value

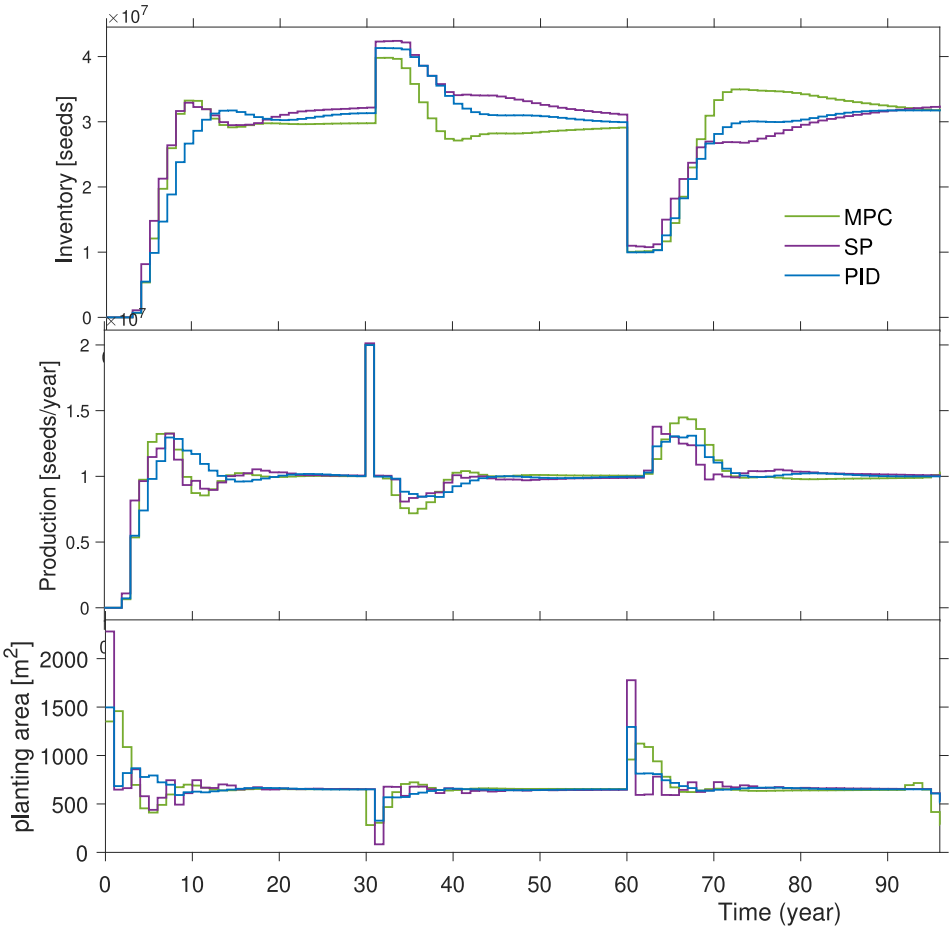


Fig. 9. Simulation results MPC SP and PID control: step response, input disturbance (of production yield), and output disturbance (of the inventory level). The seed inventory, seed production, and planting area data are for the asparagus variety K832. The rise time is nine years.

Table 1
Statistical yield- and delivery data for two varieties in the period 2010–2019 [30].

Variety	Yield/Plan		Deliveries/Forecast	
	Mean μ %	Sigma σ %	Mean μ %	Sigma σ %
K92	89	33	108	16
K93	131	37	113	13

Table 2
Monte Carlo simulation results for two varieties. MPC is superior to SP and PID for reference tracking (mean), disturbance rejection (σ^2) and percentage of non-deliveries.

Variety		K92			K93		
		MPC	SP	PID	MPC	SP	PID
Mean μ	[year]	3.0	2.3	2.3	3.1	3.8	3.7
Variance of error σ^2	[%]	0.16	0.21	0.23	0.13	0.28	0.26
Not delivered	[%]	0.2	3.0	2.5	1.3	3.0	2.2

and the distributions of outputs from the simulations, which results in indications of the performance needed to validate the developed model. Experience shows that variations in seed production of approximately 30 to 35% above and below the mean values for random variables should be considered [1].

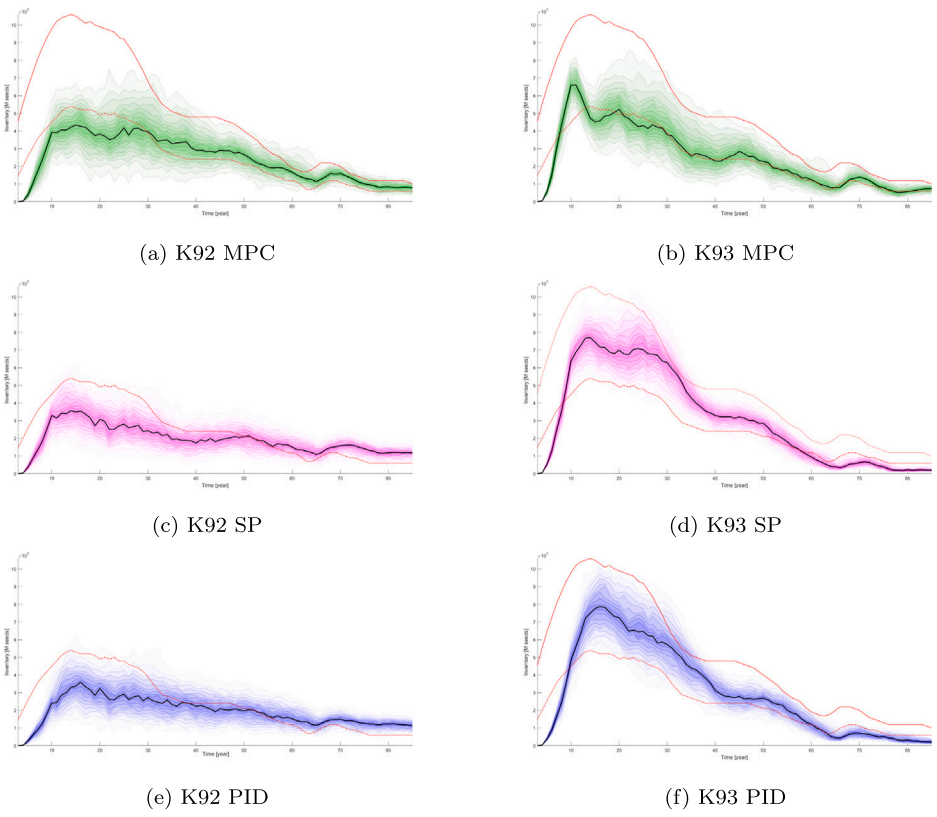
Historical statistical data in Table 1 were used to obtain the inventory levels in 10. They show the disturbance rejections and deviation from the lower and upper levels. The Monte Carlo validation test results for two varieties with 120 test runs. Table 2 summarises the results for the average inventory levels in years, the average squared error deviation from the lower level, and the average seeds that were not delivered as requested. The MPC method is superior to SP and PID for reference tracking, disturbance rejection, and deliveries. The results are depicted in Fig. 10 and Table 2.

Table 2 also indicates that the performance of SP and PID is not better than the PID controller [31], which confirms the conclusion in [32] that although there are modifications of the Smith predictor, which can avoid some of the problems of the SP for integrating processes, the performance is not better than a PID controller with the same robustness. MPC has better reference (mean) tracking and 30*to*110% better disturbance reduction compared to PID and SP PID, mainly due to full state feedback and look ahead of demand forecast and reference, which are approximated with the PID and SP PID methods.

To further demonstrate the results, the case of Fig. 1 has been 'replayed' with the historical data (forecast versus actual sales, yield, rejects and initial inventory) and is presented in Fig. 11. With the feedback–feedback method, the inventory reaches the lower level limit in 12 years and slightly undershoots it. With the Receding Horizon manual optimisation (MPC) method, the inventory reaches the lower limit in nine years, slightly overshooting the upper limit. Both methods result in no shortages and a lower cost of obsolescence due to high stocks. The historical usage of seed was reduced by using the MPC method to 42%, representing a very high capital charge improvement.

4. Discussion

Table 3 shows the differences between the three control methods. The MPC method shows better match to performance requirements, flexibility to use predefined planting areas, and implementation effort over the SP PID controller. In our scenario, the one-year planning cycle



(a) K92 MPC (b) K93 MPC

(c) K92 SP (d) K93 SP

(e) K92 PID (f) K93 PID

Fig. 10. Rejection of disturbances. Monte Carlo simulation test results for three varieties with 120 test runs. The lower reference curves indicate 3 years of stock according to the demand forecast. The upper limit curves indicate 6 years of stock, according to the risk of deterioration. Lines represent average values, and the areas that envelope the lines represent percentiles in the range of 5:10:95%.

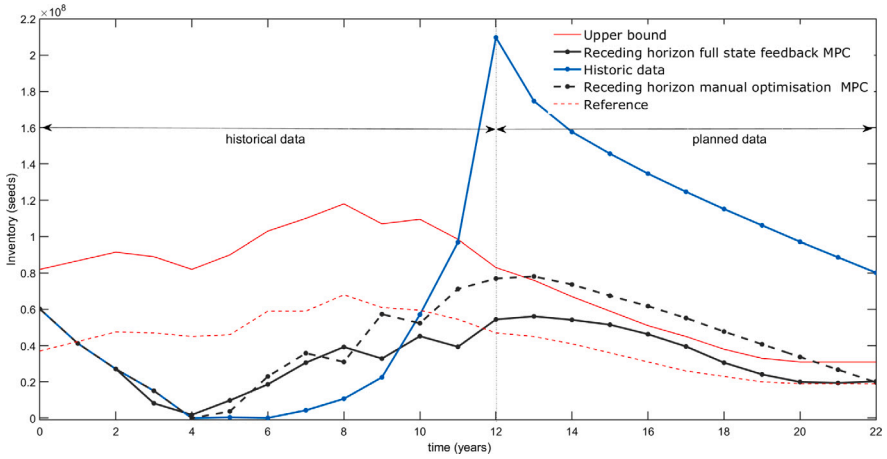


Fig. 11. Playback data comparison with historical inventory data with Receding Horizon optimal control (MPC) and Receding Horizon manual optimisation (MPC). I(0) = 60.2 million seeds. Initial planting area $\vec{x}(0) = \vec{0}$. The time period is 2006–2027. Data planned for year 12 and beyond.

spans a sufficient duration, allowing the human planner to plan for a smooth transition of the inventory level to the reference in a period of the prediction horizon 11. This semiautomatic manual MPC approach facilitates the use of predefined fixed planting areas, while using the model, the receding horizon, and the MPC look-ahead functions. The full-blown MPC method is recommended for initial planning estimates. An agricultural CRM system with all relevant crop data was used to implement the semiautomatic MPC method (see Fig. 12).

The constraints for non-negative planting areas used for the control methods show good results for inventory control, so production can be realised without the destruction of healthy plants. The receding horizon manual optimal control MPC method enables the reduction of the planted areas by destruction if needed. The strength of this method is that plant destruction is typically not needed for effective inventory control. The limited number of years available for data collection is a weakness for this research, but due to the huge variations, the results will not be significantly affected as validated by the Monte Carlo

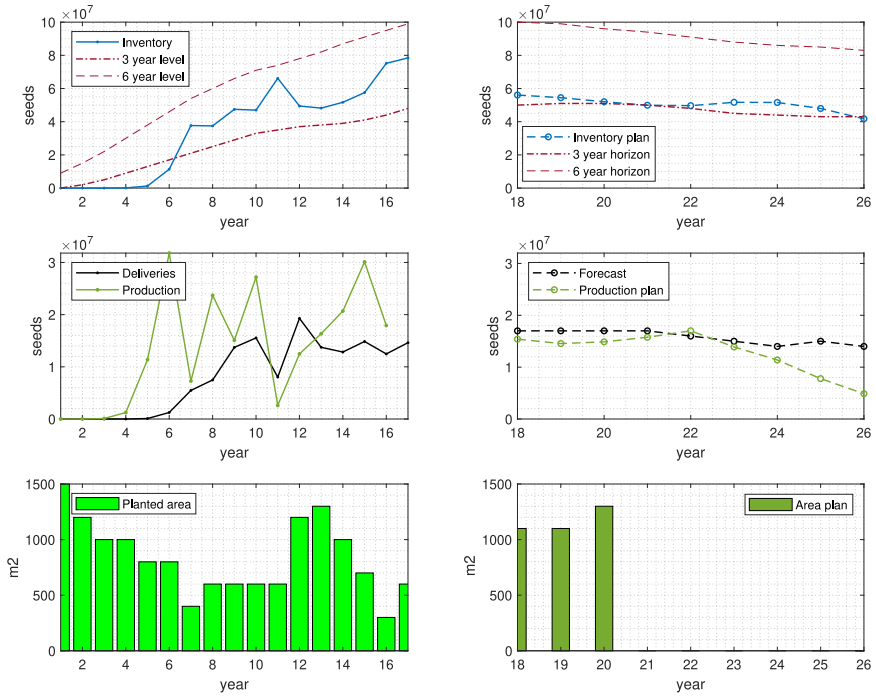


Fig. 12. Semi-automatic MPC planning dashboard for inventory, production and planting. Past data (left): Inventory level with lower and upper limits, production and deliveries, new planted area. Planned data (right): the upper figure demonstrates the planned inventory level and the limits in the receding prediction horizon of 10 years.

Table 3
Comparison of control methods. +++ : best, ++ good, + acceptable, - neutral, - poor.

Control method	Performance	Flexibility and usage of predefined planting areas	Estimated implementation effort
Receding Horizon optimal control (MPC)	+++	o	–
Receding Horizon manual optimisation (MPC)	++	++	+++
SP and PID + feedforward (SP)	+	–	++
PID + feedforward (PID)	+	–	+

simulations. Further reduction of inventory without risk of non-delivery is possible by reducing variations in production yield. Research on the influence of soil and crop care can be used for this purpose. Reducing the variations in the forecast is hard to influence as they reflect the seed markets. However, training salespeople and a yearly evaluation of sales results are recommended.

5. Conclusions

The production of perennial crop seeds is sensitive to large variations, resulting in too high stock levels and an out-of-stock risk. The literature related to production–inventory control systems in agriculture is scattered and no systems for multiperiod production dynamics, perennial crop seeds, and production (yield) rate variations have been reported.

A novel production control model is presented to describe the forecasting, planting, production, inventory and delivery cycle, which incorporates the dynamics of perennial production and the effect of a long lead time for seedling planting. The validation of the methods was performed by Monte Carlo simulation of the original crop data and a real-life replay study of historic crop data. The parameters of the model create a general approach for both annual and perennial crop seeds. To reduce variations in perennial production–inventory systems, the Receding Horizon optimal control method (MPC) with full-state feedback is found to be more effective, with superior reference tracking and $30 to 110\%$ better disturbance reduction than a feedback–feedforward PID controller and a feedback–feedforward PID controller with a Smith predictor. The Smith predictor does not improve the performance of the PID feedforward–feedback controller in the event of large parameter variations. This MPC method can be implemented in a receding-horizon manual optimal control version with lower performance but more flexibility for the planner. A real-life case study showed that perennial crop seed production inventory planning can be executed effectively by planning and control rather than by human planners to avoid cost while minimising the destruction of plants due to obsolete inventory levels.

CRediT authorship contribution statement

Robbert van der Kruk: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **René van de Molengraft:** Writing – review & editing, Project administration, Funding acquisition. **Herman Bruyninckx:** Writing – review & editing. **Eldert J. van Henten:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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