Strategic plant maintenance planning in agriculture by integrating lean principles and optimization

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Article Info

Article history:

Received May 10, 2024
Revised Jul 13, 2024
Accepted Aug 6, 2024

Keywords:

Agricultural systems
Lean principles
Mixed integer non-linear programming
Optimization
Plant maintenance planning

ABSTRACT

Operational planning within agricultural production systems plays a pivotal role in facilitating farmers' decision-making processes. This study introduces a novel mathematical model aimed at optimizing plant maintenance planning through the efficient allocation of labor, optimal utilization of machinery, and strategic scheduling. Utilizing mixed integer non-linear programming (MINLP), the model integrates lean principles to minimize waste and improve operational efficiency. The primary contributions of this study include the development of a comprehensive maintenance planning model, the application of advanced mathematical techniques in agriculture, and the enhancement of resource allocation strategies. The results demonstrate significant improvements in maintenance task scheduling, reduced downtime, and enhanced productivity, ultimately contributing to sustainable farming practices and food security. This model serves as a strategic decision-support tool for farmers, enabling data-driven planning and resource utilization to achieve both short-term efficiency and long-term agricultural viability.

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1. INTRODUCTION

Agricultural production presents farmers with numerous challenges, such as resource allocation, planting timing, maintenance operations, and harvesting, all of which significantly impact crop quality, yield, and resource utilization. Reducing resource consumption while promoting sustainable agricultural practices is essential for both economic and environmental reasons. Thus, informed decision-making regarding agricultural production and yield optimization is crucial for achieving these goals [1], [2]. At the heart of agricultural success lies operational planning, providing a structured framework for optimizing resources, managing risks, and enhancing efficiency. By systematically organizing activities, allocating resources, and anticipating challenges, operational planning enables farmers to make informed decisions throughout the production cycle. The integration of data-driven analysis, proactive risk management, and innovative technologies within operational planning not only improves productivity but also promotes sustainability and resilience in agricultural systems, contributing to long-term viability and global food security [3].

The agricultural production process can be divided into three primary stages: sowing, plant cultivation, and harvesting. Each stage requires meticulous planning and resource allocation to ensure optimal crop growth and yield. Prioritizing plant maintenance efforts is crucial for facilitating optimal plant growth and productivity, thereby ensuring favorable outcomes. Effective maintenance planning helps maintain equipment functionality and efficiency, which is essential for uninterrupted agricultural operations.

This study introduces a novel mathematical model designed to optimize plant maintenance planning within agricultural production systems. Traditional approaches to maintenance planning often lack precision and adaptability, limiting their effectiveness. Our proposed model integrates advanced mathematical techniques with domain-specific knowledge, providing a comprehensive framework for maintenance scheduling. By considering factors such as equipment usage patterns, maintenance costs, and production schedules, the model enables strategic planning of maintenance activities to minimize downtime, reduce costs, and maximize overall productivity [4]–[6].

Representing a significant advancement in agricultural operations management, our innovative mathematical model aligns with the specific requirements and constraints of agricultural production systems. By offering decision-makers insights into the timing and prioritization of maintenance tasks [7], the model facilitates proactive interventions to prevent breakdowns and ensure smooth farming operations. Ultimately, the model aims to enhance the efficiency and sustainability of agricultural activities, contributing to the broader goals of sustainable farming and food security.

Despite the critical role of operational planning in plant maintenance, scholarly literature on this subject remains limited. This paper addresses this gap by proposing an optimization-based approach to solving plant maintenance planning challenges through the development of a comprehensive plant maintenance planning model. Leveraging mixed-integer nonlinear programming (MINLP) techniques, the proposed model optimizes resource allocation and scheduling for plant maintenance activities, thereby enhancing agricultural productivity and sustainability. Our model provides a strategic tool for farmers, allowing them to make data-driven decisions that support both short-term efficiency and long-term agricultural viability.

2. THE COMPREHENSIVE THEORETICAL BASIS

The literature on operational planning for plant maintenance remains relatively limited, with existing studies primarily focusing on physiological, chemical, and physical aspects of plant growth and maintenance. However, these studies typically lack emphasis on waste reduction or comprehensive operational planning and scheduling for diverse plant maintenance tasks. Several works have addressed resource optimization in agricultural contexts. For instance, Guo *et al.* [8] presented a mathematical model for optimizing water consumption, while Adham *et al.* [9] explored the use of rainwater to enhance plant water usage efficiency. Additionally, the studies [10], [11] delved into modeling perishable biological conditions and decision-making regarding cereal crops, sugar beet, and vegetables, respectively.

Further studies have focused on production planning and optimization. Caixeta-Filho [12] proposed a model for scheduling citrus fruits, while Biswas and Pal [13] developed crop planning models aimed at minimizing inputs and operating time. Moreover, operational research techniques have been utilized to optimize harvest quantity and yield, as demonstrated by studies [14], [15]. Despite these contributions, the integration of lean manufacturing (LM) principles into crop maintenance tasks has been largely overlooked [16]–[18]. Solano *et al.* [4] noted the absence of tools for farm management akin to those used in other industries, presenting an opportunity to leverage LM principles for waste reduction.

Moreover, recent studies have highlighted the potential of combining optimization techniques with LM methodologies to enhance agricultural processes. For example, the studies [19], [20] addressed challenges in agricultural production systems such as rock removal operations, planting, and irrigation. The studies [21], [22] focused on waste reduction strategies in harvesting operations, underscoring the importance of minimizing costs associated with waste.

Furthermore, there has been a growing interest in applying Industry 4.0 technologies to agricultural processes, with researchers exploring ways to enhance efficiency and control systems. Rosales *et al.* [23] investigated the application of Lean methods in horticultural supply chains, while the studies [24], [25] proposed differentiated lean implementation frameworks tailored to small and medium farms. These studies highlight the potential of integrating modern technologies and management methodologies to optimize agricultural operations and enhance sustainability. In summary, while significant progress has been made in addressing various aspects of agricultural production and maintenance, there remains a need for further integration of optimization techniques, LM principles, and advanced technologies to achieve sustainable and efficient agricultural systems. This paper aims to contribute to this evolving field by proposing a comprehensive approach that combines MINLP with LM principles to optimize resource allocation, minimize costs, and improve operational efficiency in plant maintenance planning.

3. METHOD

The conceptual framework of a mathematical model for plant maintenance planning involves the integration of various elements and constraints to develop decision variables for maintenance operations. The model aims to optimize maintenance activities, resource allocation, and scheduling to ensure the reliability and performance of plant equipment. The proposed conceptual framework draws on mathematical optimization principles to guide the development of decision variables and constraints for maintenance planning. Additionally, the integration of lean principles and optimization in agricultural production systems offers a conceptual model for the construction of a mathematical model, emphasizing the need to consider waste products, sustainability, and agricultural operations in the development of decision variables and objective functions. The conceptual framework also considers the utilization of mathematical models and computer simulations to support effective resource allocation and decision-making in disease dynamics, highlighting the relevance of mathematical modeling in informing maintenance planning decisions. Additionally, the integration of maintenance and production planning in the conceptual framework emphasizes the development of a cost-based model for integrated planning, ensuring that maintenance strategies are effectively incorporated into production control.

The utilization of mixed integer nonlinear programming (MINLP) provides a powerful framework for encapsulating the intricacies of planning in various domains. MINLP has been applied to address complex scheduling, control, and optimization challenges in diverse fields, including chemical processes, manufacturing, energy, and infrastructure planning. The integration of MINLP enables decision-makers to consider discrete and continuous variables, nonlinear relationships, and integer constraints, offering a comprehensive approach to addressing planning complexities.

MINLP presents a complex optimization paradigm wherein certain variables are constrained to assume integer values, while both the objective function and the feasible region are delineated by nonlinear functions. This optimization technique finds extensive utility across various domains, encompassing industrial processes, financial operations, scientific management, engineering endeavors, and operations research. Integer variables serve to model logical relationships, fixed costs, piecewise linear functions, joint constraints, and indivisible resources, thus adding a layer of intricacy to the optimization process. Concurrently, nonlinear functions are indispensable for accurately capturing physical properties, covariance, and economies of scale.

MINLPs constitute a formidable class of optimization challenges owing to the confluence of integer variable optimization and nonlinear function solving. This modeling paradigm is ubiquitous in optimization, encapsulating nonlinear programming (NLP) and mixed-integer linear programming (MILP) as constituent subproblems. Expressing MINLP succinctly, it may be represented as (1).

$$\begin{aligned} &\text{Minimize} && f(x) \\ &\text{with constraint} && c(x) \leq 0 \\ & && x \in X \\ & && x_i \in \mathbb{Z}, \forall i \in I \end{aligned} \tag{1}$$

In the context where $f: \mathbb{R}^n \rightarrow \mathbb{R}$ and $c: R^n \rightarrow R^m$ represent doubly differentiable continuous functions, $X \subset \mathbb{R}^n$ denotes a finite polyhedral set, and $I \subseteq \{1,2,\cdots,n\}$ signifies a set comprising indices of integer variables, it is evident that maximization, along with more general constraints such as similarity constraints, or lower and upper bounds $l \leq c(x)\ u$, are pertinent considerations.

Problem (1) emerges as an NP-hard combinatorial challenge, owing to its inclusion of MILP, consequently necessitating traversal through a considerably vast search tree for solution determination. Moreover, nonconvex integer optimization problems are typically deemed undecidable, as demonstrated by Jeroslow [26]. The author provides instances of quadratically constrained integer programs and illustrates the inability of computational devices to compute solutions for all problems within this class. Resolving problem (1) can be achieved by either ensuring convexity of X or by presuming convexity of the problem functions.

Within the scope of this paper, $x^{(k)}$ denotes the iteration of x, while $f^k = f(x^{(k)})$ signifies the calculation of the objective function on $x^{(k)}$. The same nomenclature convention is maintained for constraints, gradients, and Hessians concerning $x^{(k)}$. Subscripts are employed to denote components, wherein x_i represents the i-th component of x. For the set $J \subset \{1,2,\cdots,n\}$, x_J corresponds to the x-component associated with J, with x_I designated as an integer variable. Additionally, $C = \{1,\cdots,n\} - I$ and x_C denote continuous variables. The dimensions of the integer space are indicated by $p = |I|$. Notably, the floor and ceiling operators are symbolized by $\lfloor x_i \rfloor$ and $\lceil x_i \rceil$, representing the largest integer less than or equal to x_i and the smallest integer greater than or equal to x_i, respectively. Given two matrices of size $n \times n$, Q and X, $X \circ Q = \sum_{i=1}^{i} \sum_{j=1}^{n} Q_{ij} X_{ij}$ represents their inner product. In general, the presence of an integer variable $x_i \in \mathbb{Z}$ leads to the feasible region of problem (1) being non-convex.

4. RESULTS AND DISCUSSION
4.1. Modelling

The plant maintenance planning problem addressed in this study encompasses several key elements, including the area designated for maintenance, a sequence of maintenance activities, and the planning horizon, all while ensuring the preservation of harvest quality. The primary objective function aims to minimize crop maintenance expenses while effectively distributing resources and scheduling tasks within the agricultural production framework. Utilizing MINLP-based models allows for the integration of pertinent parameters and variables essential to this problem domain. The following components are elucidated herein:

Assumptions:
- The designated lot or hectare for maintenance is predetermined.
- Costs associated with cultivation activities are pre-established.
- The duration and temporal window for task execution are well-defined.
- The repercussions of maintenance task failures on crop growth or subsequent harvests are understood.

Set:

I: Hectares under cultivation, $i = 1,2,3, \dots, I$
J: Stages of the process (fertilization, irrigation, and weed control.), $j = 1,2,3, \dots, J$
T: Planning periods, $t = 1,2,3, \dots, T$

Parameter:

T_{ij}: Time required to maintain hectare i in stage j
D_{it}: Lots of land i requiring labor in period t
CC_i: Cost per hectare for assessment within the optimal time window
CE_i: Cost per hectare for assessment outside the optimal time window
DH_t: Working days in period t
HC_j: Hours per crew for labor type j
TP_{jt}: Time lost by machinery in stage j during period t (irrigation system and weed control equipment.)
CC_j: Cost of hiring someone for process stage j
CD_j: Cost of firing someone for process stage j
CTP_j: Cost per unt time lost due to machinery used in process stage j

Decision variables:

X_{it}: Quantity of hectare i to be managed during normal period t (within the optimal time window)
XE_{it}: Quantity of hectare i to be managed during normal period t (outside the optimal time window)
E_{jt}: Number of available employees for stage j in period t
EC_{jt}: Number of employees to be recruited for stage j in period t
ED_{jt}: Number of employees to be fired at stage j in period t

Binary Variables:

Ω_{1t}: Variable activating one crew or group for work t (considering that shifts indicate work done at each process stage)
Ω_{2t}: Variable activating shift 2 for work t
Ω_{3t}: Variable activating shift 3 for labor t

Problem formulation:

$$\text{Min } Z = \sum_i \sum_j \sum_t \left(C_i * X_{it} + CE_i * XE_{it} + CC_j * EC_{jt} + CD_j * ED_{jt} + CTP_j * TP_{jt}\right)$$

With constraints:

$$\textstyle\sum_i T_{ij} * X_{it} - (\Omega_{1t} + \Omega_{2t} + \Omega_{3t}) * DH_t * HC * E_{jt} + TP_{jt} \le 0 \quad \forall\, j \in J, \forall\, t \in T \tag{2}$$

$$\textstyle\sum_i T_{ij} * XE_{it} - 2(\Omega_{1t} + \Omega_{2t}) * DH_t * E_{jt} \le 0 \quad \forall\, j \in J, \forall\, t \in T \tag{3}$$

$$(\Omega_{1t} + \Omega_{2t} + \Omega_{3t}) = 2 \quad \forall\, t \in T \tag{4}$$

$$E_{(j-1)t} + EC_{jt} - ED_{jt} = E_{jt} \quad \forall\, j \in J, \forall\, t \in T \tag{5}$$

$$X_{it} + XE_{it} = D_{it} \quad \forall\, i \in I, \forall\, t \in T \tag{6}$$

$$XE_{it} \geq 0 \quad \forall\, i \in I, \forall\, t \in T \tag{7}$$

$$X_{it} \geq 0 \quad \forall\, i \in I, \forall\, t \in T \tag{8}$$

Constraint (2) delineates the requirements for time loss. Constraint (3) denotes the prerequisites for conducting crop maintenance work within the optimal time window. Constraint (4) elucidates the activation requirements for shifts or work crews. Constraint (5) establishes the working requirements within specified timeframes with available employees. Constraint (6) specifies the employees needed to fulfill the required hectares to be tended. Constraints (7) and (8) indicate positive integer variables.

4.2. Algorithm

Below is the outlined optimization algorithm. Assume the following:

a. Feasible vector x satisfies $[\mathrm{B} \quad \mathrm{S} \quad \mathrm{N}]\mathrm{x} = \mathrm{b}, \mathrm{l} \leq \mathrm{x} \leq \mathrm{u}$.
b. Corresponding function value $f(x)$ and gradient vector $g(x) = [g_B \quad g_S \quad g_N]^T$.
c. Number of superbasic variables, $s(0 \leq s \leq n - m)$.
d. LU factorization of the $m \times m$ basis matrix B.
e. $R^T R$ factorization of the quasi-Newton approximation to the $s \times s$ matrix $Z^T G Z$ (Note that G, Z, and $Z^T G Z$ are never fully computed).
f. Vector rr satisfying $B^T\pi = g_B$.
g. Reduced gradient vector $h = g_s - S^T\pi$.
h. Small positive convergence tolerances TOLRG and TOLDJ.

Step 1. (Test for convergence in the current subspace). If $\|h\| > TOLRG$ go to step 3.

Step 2. ("PRICE", e.g., Estimate Lagrange multipliers, add one superbasic).
a. Calculate $\lambda = g_N - N^T\pi$
b. Choose $\lambda_{q_1} <$ –TOLDJ ($\lambda_{q_2} >$ +TOLDJ), the largest element λ corresponding to a variable below (above) its bound. If none, stop; necessary Kuhn-Tucker conditions for optimal solution met.
c. if not,
   – choose $q = q_1$ or $q = q_2$ according to $|\lambda_q| = max(\,|\lambda_{q_1}|, |\lambda_{q_2}|)$;
   – add a_q as a new column to S;
   – add λ_q as a new element to h;
   – add corresponding new column to R.
d. increment s by 1.

Step 3. (Compute search direction, $p = Zp_s$).
a. Solve $R^T R p_S = -h$.
b. Solve $LU p_B = -S p_S$.
c. set $p = \begin{bmatrix} p_B \\ p_S \\ 0 \end{bmatrix}$

Step 4. (Test ratios, "CHUZR").
a. Find $\alpha_{max} \geq 0$, the largest value of α for which $x + \alpha p$ is feasible.
b. If $\alpha_{max} \geq 0$ proceed to Step 7.

Step 5. (Line Search).
a. Find α, an approximate α*, where;

$$F(x + \alpha^* p) = \min_{0<\theta\leq\alpha_{max}}$$

b. Update x to $x + \alpha p$ and set f and g and g to their values at the new x.

Step 6. (Compute reduced gradient, $\bar{h} = Z^T g$).
a. Solve $U^T L^T \pi = g_B$.
b. Calculate new reduced gradient, $\bar{h} = g_s - S^T\pi$.
c. Modify R to reflect some recursive variable-metric changes in $R^T R$, using α, p_s and changes in reduced gradient, $\bar{h} - h$.
d. Set $h = \bar{h}$.
e. If $\alpha < \alpha_{max}$ proceed to step 1. No new constraints found, so we remain in the current subspace.

Step 7. (Change base if necessary; remove one superbasic). Here $\alpha < \alpha_{max}$ and for some $p(0 < p \leq m + s)$ the variable corresponding to column p of [B S] has reached one of its bounds.

a. If a basic variable reaches its bound ($0 < p \leq m$).
   - swap p-th and q-th columns of $\begin{bmatrix} B \\ x_B^T \end{bmatrix}$ and $\begin{bmatrix} S \\ x_S^T \end{bmatrix}$ respectively, where q is chosen to keep B nonsingular (this requires a vector πp satisfying $U^T L^T \pi_p = e_p$);
   - modify L, U, R and π to reflect these changes in B;
   - calculate new reduced gradient $h = g_s - S^T \pi$;
   - proceed to (c).
b. If not, superbasic variable reaches its bound ($m < p \leq m + s$). Determine $q = p - m$.
c. Make q-th variable in S nonbasic at the appropriate bound, thus;
   - remove q-th column from $\begin{bmatrix} S \\ x_S^T \end{bmatrix}$ and $\begin{bmatrix} R \\ h^T \end{bmatrix}$
   - return R to triangular form.
d. Decrement s by 1 and proceed to step 1.

The tables included in the paper provide essential data for understanding the optimization of plant maintenance planning. Table 1 lists the number of hectares to be cultivated during normal periods, indicating the distribution of land management tasks across different time periods. Table 2 presents the variables XE_{it}, showing the quantity of hectares managed outside the optimal time window, which may incur higher costs. Table 3 details labor allocation, including the number of laborers available, utilized, and unused across different maintenance periods. These tables collectively illustrate the model's efficiency in land use and labor distribution, supporting the goal of minimizing costs and enhancing productivity in agricultural operations.

Table 1. Number of hectares to be cultivated in normal period

X	1	2	3	4
1	350	350	350	300
2	700	700	700	750
3	300	300	300	300
4	300	300	300	410
5	300	300	300	300
6	300	300	300	300
7	300	300	310	460
8	1183.33	300	300	300

Table 2. Variables XE_{it}

XE	1	2	3	4
1	200.00000	200.00000	250.00000	200.00000
2	300.00000	300.00000	300.00000	250.00000
3	200.00000	200.00000	200.00000	150.00000

Table 3. Number of labors

K	Avail	Used	Unused
1	150.00000	450.0000	0.00000
2	150.00000	0.00000	0.00000
3	160.00000	0.00000	10.00000
4	160.00000	0.00000	0.00000

5. CONCLUSION

This paper presents a comprehensive model for plant maintenance planning aimed at minimizing production costs within agricultural operations. The proposed model encompasses the planning of labor resources, scheduling of operations, identification of maintenance areas, utilization of machinery, and the overarching objective of cost minimization for farmers. In numerous agricultural contexts, production planning is often reliant on farmers' practical expertise and empirical knowledge. However, despite the collection of relevant data, inadequate analysis frequently results in planning discrepancies, leading to elevated operational costs associated with plant maintenance and jeopardizing harvest quality. The optimization model introduced herein serves as a decision-support tool, offering systematic guidance to mitigate planning errors and optimize resource utilization effectively.

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