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Smart Landscaping Services

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Abstract. Landscaping services industry is estimated to be about $100 billion in the US. These services tend to be labor-intensive and are varied in scales ranging from single-family homes to large hospitality and leisure enterprises such as resorts and golf courses. From a management perspective the three main objectives of landscaping services are maintaining aesthetics, pest control, and lowering cost. Some of the major activities in landscaping include mowing lawns, pruning shrubs, clearing leaves, trimming hedges, and mulching. Operating cost depends on staffing level, frequency of activities, and associated fuel consumption, which have been investigated in several studies. The focus of this paper is to make landscaping services smarter by using decision-support models for managing them. Specifically, this paper proposes a two-stage optimization model for lawn mowing. The first-stage model assigns appropriate pieces of equipment and staff to various areas to minimize both operating costs and labor costs. The second-stage model optimizes the schedule of activities based on the desired due times for various areas. A numerical study is used for demonstrating the application of the decision-support model. Future direction for smart landscaping through better decision-making based on data from IoT sensors for monitoring growth, soil conditions, and weather data is also proposed.

Keywords: landscaping, workforce planning, mowing, mixed integer programming

1 Introduction

For many institutions such as universities, schools, resorts, and municipalities, it is important to maintain green areas' aesthetically pleasing and pest-free. Landscaping is labor-intensive and can require a sizable budget in these institutions. For instance, Central Park in New York City spends over $10 million for landscaping every year [1]. Some of the major activities in landscaping include mowing lawns, seasonal planting, pruning shrubs, clearing leaves, trimming hedges, fertilizing, irrigating, and mulching. Typically, lawn mowing tends to require significantly more resources than other activities and hence is the focus of this paper.

Mowing lawns at a high frequency ensures aesthetics are maintained and weeds controlled but increases associated labor and fuel cost and adverse environmental impact

[2]. It is estimated that a typical gasoline-powered lawnmower generates as much pollution as 43 cars, resulting in lawn care producing 13 billion pounds of toxic pollutants per year [3]. Moreover, for some turfgrass species, high mowing frequency kills it because it cannot produce enough leaf area for photosynthesis between mows. On the other hand, low mowing frequency can reduce the cost, but turfgrass may grow so much between mows that mowing removes too much leaf surface, leading to scalping [4, 5]. Additionally, low mowing frequency may cause a greater buildup of thatch, which in turn can cause slower microbial decomposition [2].

Some of the recent developments in mowing have mainly focused on robotic mowers, which could help in lowering costs in high-wage locations [6, 7]. However, at present and for the foreseeable future, much of lawn mowing can be expected to be largely labor-intense [8]. Thus, there is still a need for decision-support tools for lawn mowing services, especially for institutions having large green areas. Le et al. (2010) is the only paper we found that discusses a decision-making model for landscaping [1]. They developed an ant-colony heuristic algorithm to schedule maintenance activities for green areas in a university in Taiwan.

There is a need for generic mathematical models that can lead to smart landscaping services that managers use to plan and schedule activities based on resource constraints. As a first step towards such smart landscaping services, this paper proposes a two-stage optimization model for lawn mowing and its practical applicability is demonstrated through a case study. The paper is organized as follows. In section 2, the proposed mathematical model is presented. Section 3 shows the case study and the results. Section 4 proposes a futuristic smart landscape service through better decision-making based on data from IoT sensors for monitoring growth, soil conditions, and weather data. Section 5 presents conclusions and directions for future work.

2 Optimization Model for Planning and Scheduling

We decompose the lawn mowing optimization problem into two stages with the objective of minimizing operating cost and labor cost. In the first stage we assign the set of available mowing equipment and staff to various areas that need to be mowed to minimize the total cost. In the second stage the assigned tasks are scheduled to reduce tardiness.

2.1 Equipment-Technician Assignment Problem

One of the model's inputs is A areas, indexed by i, that need to be mowed. Another input is the planning span denoted by D, in days, indexed by l, $l = 1, \dots, D$. There are E types of mowing equipment and α_j pieces for type e equipment, $j = 1, \dots, E$. There are W technicians, indexed by $k = 1, \dots, W$, who have different salary costs. The optimization model is as follows.

$$Min \quad z_1 = \sum_{i=1}^{A}\sum_{j=1}^{E}\sum_{k=1}^{W}\sum_{l=1}^{D} C_j^e P_{ij} x_{ijkl} + \sum_{j=1}^{E}\sum_{k=1}^{W}\sum_{l=1}^{D} C_k^r t_{jkl}^r + C_k^o t_{jkl}^o \qquad (1\text{-}1)$$

$$s.t.\quad \sum_{j=1}^{E}\sum_{k=1}^{W}\sum_{l=1}^{D} x_{ijkl} = 1, \qquad \forall\, i \qquad (1\text{-}2)$$

$$\sum_{i=1}^{A}\sum_{l=1}^{D} x_{ijkl} \le M\Delta_{jk}, \qquad \forall k \qquad (1\text{-}3)$$

$$\sum_{l=1}^{D} \delta_{il} = 1, \qquad \forall\, i \qquad (1\text{-}4)$$

$$\sum_{j=1}^{E}\sum_{k=1}^{W} x_{ijkl} = \delta_{il}, \qquad \forall\, i, l \qquad (1\text{-}5)$$

$$\sum_{i=1}^{A} P_{ij} x_{ijkl} = t_{jkl}^{r} + t_{jkl}^{o}, \qquad \forall\, j, k, l \qquad (1\text{-}6)$$

$$t_{jkl}^{r} \le T^{r} n_{jkl}, \qquad \forall j, k, l \qquad (1\text{-}7)$$

$$t_{jkl}^{o} \le T^{o} n_{jkl}, \qquad \forall j, k, l \qquad (1\text{-}8)$$

$$\sum_{k=1}^{W} n_{jkl} \le \alpha_{jl}, \qquad \forall\, j, l \qquad (1\text{-}9)$$

$$\sum_{j=1}^{E} n_{jkl} \le 1, \qquad \forall\, k, l \qquad (1\text{-}10)$$

$$x_{ijlk}, \delta_{il} \in \{0,1\};\; t_{jkl}^{r}, t_{jkl}^{o} \ge 0;\; n_{jkl} \in \{0\} \cup \mathbb{N}$$

Eq. (1-1) is the objective function to minimize equipment operation costs and labor costs. C_j^e is the hourly cost of equipment j including fuel cost; or equipment rental and fuel cost. P_{ij} is the hours to mow area i by using equipment j. C_k^r and C_k^o are the unit labor cost in regular hours and overtime, respectively. The decision variable x_{ijkl} is a binary variable which indicates equipment-technician pair (j/k) is used for mowing area i on day l. Other two decision variables, t_{jkl}^r and t_{jkl}^o, are the number of regular hours and overtime hours, respectively, used in day l of worker type k using equipment j.

Eq. (1-2) ensures that all areas are mowed by assigning one equipment-technician pair to every area. Eq. (1-3) describes technican capability for operating a specicific type of equipment; Δ_{jk} is equal to one if technician j is able to operation equipment type k; M is a sufficient large contant. Eq. (1-4) and Eq. (1-5) decides the day for mowing an area where variable δ_{il} is set to 1 if area i is cleared on day l. Eq. (1-6) constrains the total time that a piece of equipment is used to match the available hours of the assigned technician. Eq. (1-7) and (1-8) constrain the time assigned for a technician is within allowable limits of regular and overtime hours denoted by T^r and T^o, respectively. The number of available pairs of equipment-technician (j/k) on day l is denoted by n_{jkl}. Eq. (1-9) restricts the pieces of type k equipment assigned on day l should not exceed the number available. Eq. (1-10) constrains that one technician can be only assigned to at most one piece of equipment in a day. It should be noted that the model assumes the technicians are available all the time during the planning period, and this assumption holds for some organizations. The assumption can be relaxed by substituting T^r with T^o to T^r_{kl} and T^o_{kl}, which allows some technicians have a tolerance for working on other tasks.

2.2 Workforce Scheduling Problem

Based on the optimal assignment, the second stage optimization model tries to schedule the tasks to be completed before the due time of each area. It can be especially essential when there are periodic pedestrian traffics that would making mowing inconvenient and inefficient. Here we assume that the initial schedule of each technicians is blank. Define m and n are index aliases of i. C^d_m is the tardiness cost for area m. P_m is the optimal process time for area m from the result of stage one. The scheduling model for an equipment-technician pair (j/k) on day l is shown below.

$$Min \quad z_2 = \sum_{m=1}^{A} C^d_m d^+_m \tag{2-1}$$

$$s.t. \quad v_m = s_m + P_m \qquad m = 1, \dots, A \tag{2-2}$$

$$d^+_m - d^-_m = v_m - DT_m, \qquad m = 1, \dots, A \tag{2-3}$$

$$s_m \geq v_n - M\delta_{mn}, \qquad m = 1, \dots, A;\ n = 1, \dots, A;\ m \neq n \tag{2-4}$$

$$s_n \geq v_m + M(\delta_{mn} - 1), \qquad m = 1, \dots, A; n = 1, \dots, A;\ m \neq n \tag{2-5}$$

$$\delta_{mn} + \delta_{nm} = 1, \qquad m = 1, \dots, A; n = 1, \dots, A;\ m \neq n \tag{2-6}$$

$$\delta_{mn} = \{0,1\}, \qquad m = 1, \dots, A; n = 1, \dots, A;\ m \neq n$$

$$v_m, s_m, d^+_m, d^-_m \geq 0, \qquad m = 1, \dots, A$$

The objective function (2-1) is to minimize the costs of tardiness. Eq. (2-2) calculates the completion time of each task. Eq. (2-3) is the tardiness constraint, where d^+_m is zero if the task is scheduled earlier than due time, otherwise, d^-_m is zero. DT_i is the due time of the task in area i. Eq. (2-4) and (2-5) are the schedule constraints that determine the order of the tasks, where M is a sufficiently large number. If the technician mows area m before area n ($\delta_{mn} = 1$), it will activate Eq. (2-5) and release Eq. (2-4), and vice versa. Eq. (2-6) makes sure the consistency of the schedule.

3 Case Study

A large institution (name withheld) has 30 areas that need to be mowed. The operation team has three technicians and four pieces of equipment available to perform the tasks every day. Based on the records, the operating time p_{ij} of each type of equipment for each area can be obtained. The planning span is from Monday to Wednesday ($L = 3$), and the cost of labor and equipment are shown in Table 1. In the second stage, the due time for each task is set to be eight hours, and the tardiness cost c_m^d is one in order to minimize the overtime labor hours. In this study, techincans can operate all types of euqipments, which means $\Delta_{jk} = 1$ for all j.

Table 1. Hourly Rate of Technician and Equipment

Technician (k)	Regular hour cost (c_k^r)	Overtime cost (c_k^o)
Tech1	\$25.00	\$37.50
Tech2	\$28.00	\$42.00
Tech3	\$31.00	\$46.50

Equipment (j)	Hourly cost (c_j^e)	Availability (α_j)
Equip1	\$74.00	1
Equip2	\$51.00	2
Equip3	\$80.00	1

The problem is solved by CPLEX/GAMS solver on NEOS [9], and the relative optimality criterion is set to be 0.01. This particular formulation for the application is solved in less than one minute, which is adequate for the purpose of daily or weekly use. The resulting solution is illustrated in Fig. 1. The optimal cost, consisting of operating costs and labor costs, is 5669.31. The corresponding total time required is 62.66 hours, and the total tardiness is 3.82 hours.

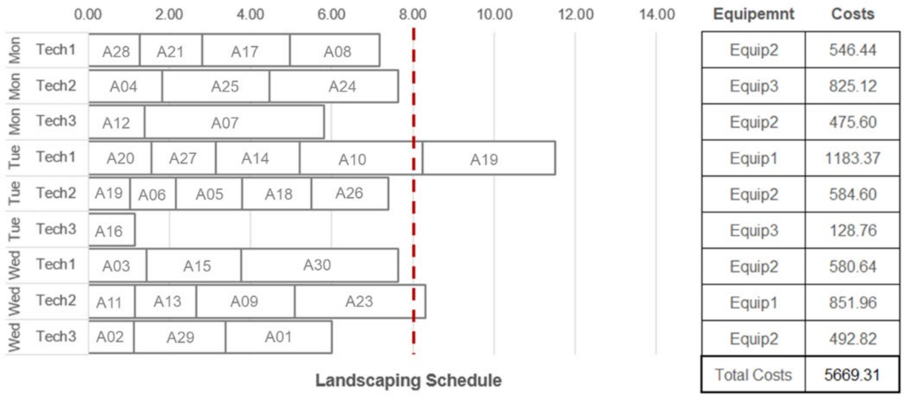

Fig. 1. Computational Results

4 IoT-Driven Models for Smart Landscaping

Now there is a slew of affordable and easy-to-use networked sensors as a part of the IoT (Internet-of-Things) megatrend. These IoT sensors can be networked wirelessly, which makes them very attractive for innovating landscaping services, and enabling their digital transformation towards smart landscaping systems. For instance, a first step would be use IoT GPS trackers mounted on mowing equipment to accurately estimate the time required to mow a specific area. Such IoT GPS trackers would be an early step in digitizing the process to acquire key performance data (P_{ij} in the models above) instead of relying on experience-based guesstimates or expensive manual time studies. As in **Fig. 2**, using GPS trackers, the measurements from sensors, types of equipment used, and actual operation time of each area will be gathered and stored in a database. These records coupled with weather data can establish a regression model to predict operation times (P_{ij}). Moreover, such a digitized smart system will provide new insights in terms of how P_{ij} is influenced by factors such as time-of-day, specific technician, weather, and seasonality, enabling higher fidelity models and more effective decisions. Similarly, low-cost soil sensors coupled with weather data can be used to predict grass growth and optimize lawn mowing frequency that takes into turfgrass health and environmental considerations. The resulting models and decision-support systems will help make landscaping services smarter than in the current manual, labor-intense operations or for a fleet of robotic lawn mowers in the future.

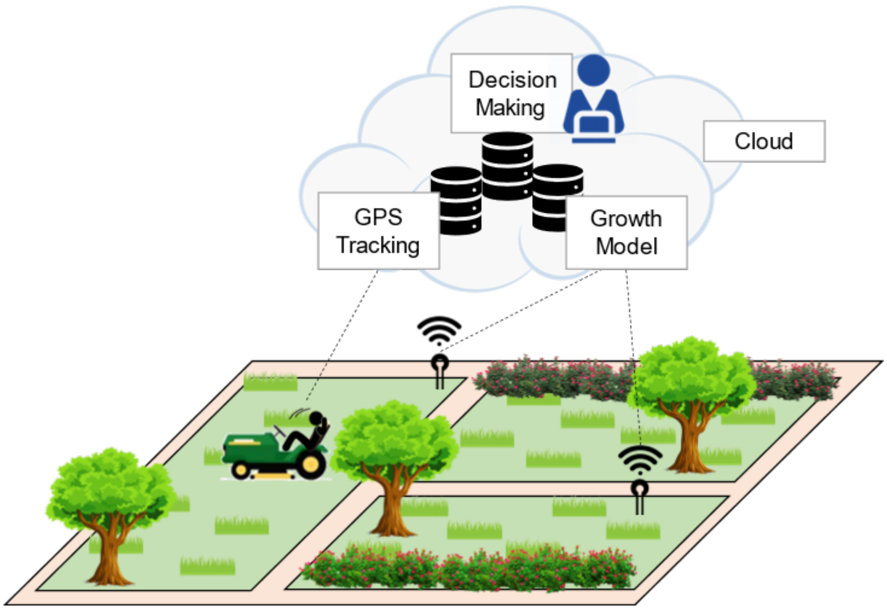

Fig. 2. Smart Landscaping Services

5 Conclusion

Maintaining green areas is important for many organizations since the green area provides water filtration, temperature regulation, carbon dioxide absorption, oxygen release into the atmosphere, and aesthetics. However, only a few studies have focused on models for decision-making in landscaping services. This paper proposes a two-stage optimization model. In the first stage, the model assigns appropriate equipment-technician pairs to various areas considering their availability and efficiency to minimize operating and labor costs. In the second stage, the activities are scheduled optimally so that any tardiness is minimized and provide the start time for each activity. Scheduling of mowing activities may be necessary in practice when there are considerable pedestrian traffics at different times of the day or days of the week.

A case study is used to demonstrate the usage of the model in a relatively small scale to illustrate the opportunity for making such labor-intense services smarter. It should be noted that in this model we assume that every technician only operates one equipment on any given day (constraint (1-9)). In practice, a technician may operate multiple equipment if they have time available, and in such situations the optimal cost generated by the model should be treated as an upper bound because the real cost will be lower. This issue can be addressed in the future by increasing the granularity of the time period from one day to hours but this may take longer to compute the solution for large-scale problems. This issue could also be addressed by reformulating the constraints in the model.

Future works will expand the model to include other significant activities in landscaping services such as pruning shrubs and leaf cleaning to provide a more comprehensive solution. IoT-driven models for smart landscaping services (**Fig. 2**) present a fertile opportunity to fully engineer these processes and leverage technological advances to improve the productivity of these services.

	DESCRIPTION
$\boldsymbol{C_j^e}$	The hourly cost of equipment j including fuel cost; or equipment and fuel cost.
$\boldsymbol{C_k^r}$	The regular hourly cost of technician k
$\boldsymbol{C_k^o}$	The overtime hourly cost of technician k
$\boldsymbol{P_{ij}}$	The hours to mow area i by using equipment j.
$\boldsymbol{T^r}$	The allowable regular time hours of a technician
$\boldsymbol{T^o}$	The allowable overtime hours of a technician
$\boldsymbol{x_{ijkl}}$	The binary variable indicating equipment-technician pair (j/k) is used for mowing area i on day l.
$\boldsymbol{t_{jkl}^r}$	The regular hour used for equipment-technician pair (j/k) on day l
$\boldsymbol{t_{jkl}^o}$	The overtime used for equipment-technician pair (j/k) on day l
$\boldsymbol{\Delta_{jk}}$	The binary parameter indicator representing whether techincan can operate equipment type j or not.
$\boldsymbol{\delta_{il}}$	A binary variable indicating if area i is cleared on day l
$\boldsymbol{n_{jkl}}$	The number of pairs of equipment-technician(j/k) on day l
$\boldsymbol{\alpha_{jl}}$	The total available equipment j on day l
$\boldsymbol{C_m^d}$	The tardiness cost of area m
$\boldsymbol{d_m^+}$	The tardiness variable of area m

$\boldsymbol{d_m^-}$	The earliness variable of area m
$\boldsymbol{v_m}$	The completion time of area m
$\boldsymbol{s_m}$	The start time of area m
$\boldsymbol{P_m}$	The process time of area m (from model 1)
$\boldsymbol{DT_m}$	Due-time of area m
$\boldsymbol{\delta_{mn}}$	The binary variable indicating if area m is cleared before area n
	Note I, m, n are alias indices of area; j is the index of equipment types; k is the index of technicians; l is the index of planning days

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