Algorithmically-Guided Postharvest Protocols by Experimental Combinatorial Optimization

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ABSTRACT

The application of search and learning to experimental domains, where the objective function cannot be accurately simulated, but rather requires a measurement in real industrial settings, lies in the focus of this study. We consider the problem of devising treatment protocols for fresh cucumbers, whose quality rapidly deteriorates once being harvested, by considering the combinatorial space of possible postharvest practices. The overall target is to prescribe a combination of treatments, with specified activation levels, that minimizes the cucumbers' quality loss after 4 weeks in two storage environments: 10°C and 20°C. This study engaged with a postharvest laboratory with industrial settings to research and develop a sequential experimentation procedure, in a closed feedback-loop fashion, and subject to strict budget and timeline constraints. The laboratory measurements comprise the assay of color, stiffness and mass, as well as external blemishes – in both *harvest* and *post-4-weeks* points in time. Their deviations constitute the aggregated objective function that undergoes minimization for both temperatures. After formulating the optimization problem, we outline our approach and report on the attained results. The obtained protocols significantly outperform the best-known human reference practice, and their nature is visualized and analyzed. Finally, we mention the impact and outlook for industry.

CCS CONCEPTS

• **Computing methodologies → Model development and analysis**; **Randomized search**; *Discrete space search*; *Artificial intelligence*; • **Applied computing**;

KEYWORDS

Agro/Food Industry, Sequential Experimentation, Discrete Evolution Strategy, *Cucumis sativus L.*, Cucumbers, Farm-to-Fork

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1 INTRODUCTION

Optimization problems and machine-learning tasks are increasingly recognized as *game-changers* in active research of experimental systems within the Sciences and Engineering, in Academia and Industry. Combinatorial Optimization (CO) is one of the most challenging problem-domains in the Computer Science field. Its applications cover a broad spectrum of everyday's life: navigation and scheduling, drug discovery and medical research, as well as cutting-edge electro-optical technologies, to name only a few. The application of CO to experimental domains, where the objective functions cannot be calculated nor simulated, but rather require real-world field/laboratory measurements, lies in the focus of this study. The majority of experimental sciences share the common basis of physical observables that may play the role of objective functions to be optimized. Scientists aim at optimal behavior of their systems and arriving at new discoveries while navigating the landscape of possible experiments. This perspective reduces any scientific discovery to solving a CO problem [18]. At the same time, algorithms and metaheuristics have been widely applied to global optimization of complex models, whose objective function either possesses an explicit expression or can be represented by a computer-based model. In contrast to computing the objective function, there are also many applications of global optimization which require real-world experimentations for quality evaluation [36]. Examples include but are not limited to combinatorial drug discovery [4], enzymes production [40], as well as recent attempts to optimize protein expression [9]. Furthermore, statistics-based approaches are considered to be the gold standard in the domain of experimentation, particularly the family of Optimal Design procedures and the Design-of-Experiments (DoE) methodology [2, 14]. The applicability of Evolutionary Algorithms (EAs) to experimental optimization has already been demonstrated in the early days of the Evolutionary Computation field [34]. In recent years, EAs have been successfully utilized in a number of studies on experimental optimization within the Natural Sciences [36].

The collection of practices for handling crops immediately following their harvest, with the explicit goal of maintaining their agricultural quality while boosting their shelf-life, is referred to as postharvest. Postharvest technologies [21] constitute a cornerstone of modern sustainability, having a direct influence on food security, with a potentially vast economical impact on the global Agro/Food industries. Nevertheless, they impose grand scientific challenges concerning treatment protocols of fresh fruit and vegetables. The demand for affordable food supply is growing in order to meet the increase of world population as described by the Food and Agriculture organization of the United Nations (FAO) [11]. A recent organized effort to meet these *food security* demands is the so-called Farm-to-Fork strategy of the European Union[1]. It was reported that postharvest losses within highly developed food systems (developed countries) might reach 20% and it was estimated that 30% and even more of food losses occur in less developed systems [37]. Therefore, reduction of postharvest food losses would improve food security by an impact on food access and utilization. Improved postharvest practices can provide solutions to challenges identified by the FAO that are related to food stability and availability, making food systems more efficient [3].

Freshly harvested fruit and vegetables consist of high water content and are therefore susceptible to physiological and pathological postharvest deterioration. The Cucumber (*Cucumis sativus L.*) is a crop with a high economic value, which constitutes a good source for antioxidants, magnesium, vitamin C and dietary fibers [35]. The cucumber fruit typically contains 95% of water and has a limited postharvest potential of less than 14 days of storage due to mass loss, discoloration of the peel, softening, fungal infections, and other visual defects.[2] Cucumbers are very sensitive to *chilling injuries* when stored at temperatures below 7°C∼ 10°C (cultivar-dependent) [5], developing water-soaked areas, pitting and accelerated decay. They are also highly sensitive to exogenous ethylene (low levels as 1-5 p.p.m.), which accelerates yellowing and decay during storage and distribution [39]. Hence, extending the postharvest shelf-life of cucumbers constitutes a significant real-world challenge. Various postharvest treatments were previously examined to improve the cucumbers' quality: short hot water dipping [25], modified atmosphere packaging [16, 22, 27], edible coatings [28], amino acids [13], ozone [24], UV-A radiation [17], plant growth regulators [5, 26], and more. The reported studies investigated the application of a single factor on cucumbers and its impact on postharvest qualities and potential. In order to achieve a synergistic effect of the treatments on the postharvest fruit quality, the current study aims to examine a consecutive application of a couple of postharvest treatments as well as a packaging, by means of CO.

Indeed, optimization approaches have been widely applied to food security challenges in recent years. One particular domain that has enjoyed the benefits of optimization is food supply-chain management (see, e.g., [10, 12]). However, to the best of our knowledge, an attempt to apply experimental CO to a collection of postharvest treatments has never been reported in the literature. Furthermore, beyond the scope of food security optimization, we also foresee the development of robotics-based automation in postharvest operations. Therefore, we are particularly interested in laying foundations for Artificial Intelligence that will guide such automation in the long term. To this end, we target relevant real-world settings by considering two environments: 10°C to represent a typical storage system, and 20°C to represent the typical temperature in the common supermarket.

Contribution and Paper Organization

The concrete contributions of this paper are the following:

- We formulate the postharvest quality loss problem and introduce a combinatorial optimization perspective to it.
- We describe in detail an experimental platform of cucumbers' postharvest and present optimization results of two 4-weeks storage systems: 10°C and 20°C – subject to a timeline of 7 iterations and overall ∼80 evaluations per each system.

The remainder of this paper is organized as follows. Next, Section 2 formulates the problem, followed by Section 3, which describes the approaches that we take to address it and specifies the setup. The experimental observations are reported and analyzed thereafter in Section 4. Finally, Section 5 summarizes this study and discusses generalizations and future pathways.

2 PROBLEM FORMULATION

We pose the *research question* that we target:

> Is it possible to devise postharvest treatment protocols for fresh products as a CO problem, when laboratory measurements constitute the objective function?

Next, we formulate the problem and present our notation.

Search Space Definition

Given n_t postharvest *treatments*, as well as a set of postharvest *packages*, the generalized CO problem is defined by (n_t+1)-dimensional decision variable vectors, denoted as $\vec{\tau}$, representing candidate postharvest protocols. These vectors encompass integer variables, and represent permutations over combinations that subscribe to a discrete (mixed nominal and categorical) space $\mathcal{T}$:

$$\vec{\tau} \in \pi \circ \mathcal{T}, \quad \pi \in P_{\pi}^{(n_t)}, \quad \mathcal{T} = \mathcal{T}_1 \times \mathcal{T}_2 \times \cdots \times \mathcal{T}_{n_t} \times \mathcal{P}, \tag{1}$$

where $P_{\pi}^{(n_t)}$ denotes the set of permutations of length n_t. $\mathcal{T}_j$ lists the levels/categories of the j^{th} variable/treatment, i.e., $\forall j = 1, \ldots n_t \; \tau_j \in \mathcal{T}_j$, with each variable having an independent cardinality $\left|\mathcal{T}_j\right|$. Notably, even when a variable is perceived as a continuous laboratory parameter (sometimes referred to as *control*), we consider herein its discretization to be mapped by a range of integers, e.g., $\left[\mathcal{T}_j^{\min}, \ldots, \mathcal{T}_j^{\max}\right]$ per τ_j. We define the 0^{th} level/category of each treatment as an indicator for inactivity, that is, $\tau_j = 0$ implies that the j^{th} treatment is inactive within the current protocol. Finally, $\mathcal{P}$ denotes the packaging category, which prescribes a certain postharvest **package** after the treatments' application (i.e., holding the treated object throughout the storage period): $\tau_{n_t+1} \in \mathcal{P}$. Altogether, the cardinality of this generalized search-space reads

$$|\pi \circ \mathcal{T}| = n_t! \cdot \left[\prod_{j=1}^{n_t} \left(\mathcal{T}_j^{\max} - \mathcal{T}_j^{\min}\right)\right] \cdot |\mathcal{P}| \,. \tag{2}$$

In practice, this generalized form may be constrained when a limitation is posed on the number of active treatments. In such a scenario, when considering (1), it will translate into a constraint on the number of zero values within a feasible candidate combination.

Objective Function Definition

The primary goal is to maintain the fresh product's qualities as recorded at the harvest point in time (i.e., day 0), denoted as state i, when compared to their assay after a predefined period (e.g.,

[1] https://ec.europa.eu/food/horizontal-topics/farm-fork-strategy_en
[2] https://postharvest.ucdavis.edu

4 weeks), denoted as state f. Upon quantification of the assays, the desired outcome is the minimal deviation of all quantities. In particular, we are interested in four qualities and their scores:

(1) Color: the peel color change was objectively evaluated using the Amilon^{TM} (Isolcell, Italia) and the Minolta^{TM} (Japan) surface color meters. Our assay measures the L*a*b* and L*C*h* color spaces, and the color of state ℓ is calculated as follows (the justification exceeds the scope of this paper):

$$c_\ell := \left(L^* + a^* + b^* + h^*\right)_{\text{Amilon}} + \left(L^* + a^* + b^* + C + h^*\right)_{\text{Minolta}} .$$

Then, the deviation from the color of the initial state i to the recorded color at state f is defined as the following normalized *unitless* term:

$$\Delta c\left(\vec{\tau}\right) := \left|c_f\left(\vec{\tau}\right) - c_i\right| / c_i .$$

(2) Stiffness: the softening of the fruit was evaluated by measuring the stiffness of the fruit with fruit texture analyzer GS-15 (Guss, South Africa). It is measured in Newtons per meter, $[s_i] = \frac{\text{N}}{\text{m}}$, we are interested in the normalized *unitless* stiffness deviation –

$$\Delta s\left(\vec{\tau}\right) := \left|s_f\left(\vec{\tau}\right) - s_i\right| / s_i .$$

(3) Mass: measured in kg, $[m_i] = \text{kg}$, we are interested in the normalized *unitless* mass deviation –

$$\Delta m\left(\vec{\tau}\right) := \left|m_f\left(\vec{\tau}\right) - m_i\right| / m_i .$$

(4) Expert's score: trained personnel evaluated the severity of different external blemishes including: shriveling, peel frictions and scars (in the scale of 0-5). An overall quality evaluation estimated the commercial quality[3] of each fruit (in the scale of 0-10). Rotten fruit was marked and was discarded. The overall score is normalized within $[0, 1]$ and denoted as $\text{score}_{\text{exp}}$. Due to its subjectivity, this score was evaluated by an immutable set of researchers. In the future, this score will be replaced by an automated photography-based scoring mechanism, which is currently under development.

Due to resources limitation, we are considering a single-objective aggregation of the aforementioned quantitative deviations, despite known drawbacks of this approach (see, e.g., [6]). Explicitly, we target the following objective function:

$$\mathcal{L}_{i\to f}\left(\vec{\tau}\right) := \Delta c\left(\vec{\tau}\right) + \Delta s\left(\vec{\tau}\right) + \Delta m\left(\vec{\tau}\right) + \text{score}_{\text{exp}}\left(\vec{\tau}\right) \mapsto \min \ . \quad (3)$$

Optimization Problem Synopsis

Our setup dictates the usage of only 2 treatments per protocol, which is also pragmatic for potential commercial applications. Overall, the targeted optimization problem may be formulated as follows – given a combinatorial search-space of possible postharvest treatments and packages $\mathcal{T}$, obtain a protocol $\vec{\tau}^*$ of 2 treatments and a package that minimizes the following loss function as long as the product is not rotten (there is no observed decay):

$$\boxed{\begin{array}{ll} \text{minimize}_{\vec{\tau}\in\pi\circ\mathcal{T}} & \mathcal{L}_{i\to f}\left(\vec{\tau}\right) \\ \text{subject to:} & \#\left\{j : \tau_j \neq 0,\ j = 1,\ldots,n_t\right\} == 2, \\ & \{\text{decay} < \epsilon\} \end{array}} \quad (4)$$

[3]The quality parameters were established according to UCDAVIS quality definitions, https://postharvest.ucdavis.edu, and the USDA parameters for cucumbers [38].

In our reported cucumbers' case-study there are $n_t = 10$ possible treatments and $|\mathcal{P}| = 3$ packaging types, so the overall search-space cardinality is reduced to

$$10 \cdot 9 \cdot 3 \cdot |\mathcal{T}|_{1:n_t} \cdot |\mathcal{T}|_{2:n_t} \approx 10^6,$$

(when the variables' cardinalities are sorted in a descending order) in comparison to $\sim 10^{17}$ of the generalized problem in light of (2). Importantly, the current study considers 2 instantiations of (4) per different storage environments, 10°C and 20°C. In essence, different search landscapes underlie each environment/system [30], and thus we are practically addressing 2 optimization problems.

3 APPROACH AND SETUP

3.1 Compact Representation

Given the hard constraint to devise only 2 treatments, i.e., $\#\left\{j : \tau_j \neq 0,\ j = 1,\ldots,n_t\right\} == 2$, we choose to allocate 3 decision variables for indicating the treatments and the packaging, alongside 2 additional decision variables for indicating the activation levels of the treatments. Given the fact that all the levels in our experimental setup are *nominal*, we altogether represent a candidate solution using 3 categorical variables and 2 integers. We denote a candidate protocol subscribing to this representation as $\vec{\varphi}$:

$$\vec{\varphi} := \left(\overbrace{1^{st}\ \text{treatment},\ 2^{nd}\ \text{treatment}, \text{package},}^{\vec{d}\text{: categorical}}\ \overbrace{1^{st}\ \text{level}, 2^{nd}\ \text{level}}^{\vec{z}\text{: integers}}\right)^T . \quad (5)$$

In practice, this consideration induces a 5-dimensional search-space, rather than the original 11-dimensional space with the excessive number of equality-to-zero constraints.

3.2 Strategy: Discrete ES

Due to the limited population size, we capitalize on Mixed-Integer Evolution Strategies (MIES) [33], which are known to excel under such conditions. We employ a self-adaptive mutation operator that relies on strategy parameters carried by each individual. The application to the categorical variables $\vec{d}$ utilizes a strategy parameter $p_d \in [0, 1]$, initialized uniformly randomly, whereas the application to the integers $\vec{z}$ utilizes a strategy vector $\vec{q}$ that is initialized by $\vec{q} := \left(q_j = \left(\mathcal{T}_j^{\max} - \mathcal{T}_j^{\min}\right) / \sqrt{2}\right)^T$. The details concerning the mutation operator, entitled `DiscreteESmutate`, are provided in Algorithm 1, which is specifically prescribed according to our compact representation of $\vec{\varphi}$ (5) (i.e., size($\vec{d}$) = 3). Importantly, all visited search-points are recorded in an archive, and the mutation operator is called in a `while` loop until a new point is reached (i.e., revisiting is prohibited, similarly to Tabu search, when considering the 5-dimensional $\vec{\varphi}$).

Furthermore, the recombination operator is applied only with a probability $p_c = 0.1$ – *discrete recombination* is applied to the decision variables, whilst intermediate recombination is applied to the strategy parameter. Altogether, our implementation and parameter settings mostly followed [32], except for handling the specific constraints (e.g., treatments' duplicates), and for setting the population size according to the experimental setup.

```
DiscreteESmutate(d⃗, p_d, z⃗, q⃗)
    /* categorical decision variables */
    τ^(d) ← 1/√6
    p'_d ⟵ 1/[1 + (1−p_d)/p_d · exp{−τ^(d) · N(0,1)}]
    p'_d ⟵ enforce value within [p_min, 1/2]
    for j = [1,2,3] do
        if U(0,1) < p'_d then
            do
                d'_j ←
                  { uniformly randomly from |T|,   if j < 3
                  { uniformly randomly from |P|,   otherwise.
            while d'_j == d_j
        end
    end
    while d'_1 == d'_2 do
        d'_2 ← uniformly randomly from |T|
    end
    /* integer decision variables */
    N_g ← N(0,1), τ_g^(z) ← 1/2, τ_ℓ^(z) ← 1/√(2·√2)
    for j = [1,2] do
        q'_j ⟵ q_j · exp{τ_g^(z) · N_g + τ_ℓ^(z) · N(0,1)}
        if d'_j ≠ d_j then
            z'_j ⟵ uniformly randomly from T_j
        else
            z'_j ⟵ z_j + G(0, q'_j)
        end
    end
    return {d⃗', p'_d, z⃗', q⃗'}
```

Algorithm 1: MIES-based self-adaptive mutation operator utilized by the Discrete ES: $\left\{\vec{d}, p_d\right\}$ are the (categorical) decision variables and the strategy parameter, respectively, where $d_1, d_2 \in \{1, \ldots, |\mathcal{T}|\}$ represent the selected treatments, and $d3 \in \{1, \ldots, |\mathcal{P}|\}$ represents the packaging. $\{\vec{z}, \vec{q}\}$ are the integer decision variables and strategy parameters, respectively, with $\{z_1, z_2\}$ represent the activation level of the selected treatments $\{d_1, d_2\}$. $\mathcal{N}$, $\mathcal{G}$, and $\mathcal{U}$ denote the normal, geometric and uniform distributions, respectively. Finally, $p_{\min}$ is the lower bound of p_d.

3.3 Setup

We describe the technical specifications of our experimental setup.

Postharvest Treatments. We consider the following postharvest treatments (in alphabetical order): 1-MCP (1-methylcyclopropene), Blush (Prohydrojasmon propyl-3-oxo-2-pentylcyclo-pentylacetate), Cytokinin (Benzyl adenine 6), Deccoscald (Ethoxyquin), Edible coating (combinations of D-Glucose and Starch), Gibberellin (GA3), Hexanal, Hot-Water-Dipping followed by Hydrocooling, UV-C radiation (254nm), and Wax (Carnauba). The packaging types were LDPE (Low density polyethylene), RopBAG (Cast polypropylene) and ZoeBAG.

Budget, Population and Repetitions. The implementation of the protocols as well as the comprehensive post-storage measurements constitute a dramatic operational effort in the laboratory. In practice, a timeline of 7 iterations was approved in the laboratory's program, and an overall experimental budget of 26 protocols was granted per each iteration – accounting for the two systems and the need for a *biological repetition.* This budget breaks down in each system to a population of $\mu = 11$ algorithmically-guided candidate protocols plus two additional references: a baseline untreated fruit ("control", denoted as $\vec{\tau}_0$), and the "in-house protocol" (a home-brewed protocol that has proven successful, following a preliminary set of experiments using a single treatment and packaging; denoted as $\vec{\tau}_{\text{ih}}$). Each of the 13 protocols is implemented on 10 fruit, to establish *biological repetition.* Following the implementation, the packaged fruit are stored for 4 weeks in either 10°C or 20°C refrigeration.

Averaging and Value Determination. Following the storage period, the fruit are unpacked and thoroughly assayed. The aggregated objective function value per each candidate protocol $\vec{\tau}$, $\mathcal{L}_{i\to f}(\vec{\tau})$ (3), is calculated as the average of all its repetitions (rotten fruit are discarded while being a minority, otherwise result in a penalty). Since the evolutionary heuristic relies only on the ranking of the individuals per each generation, the raw values are used in their current form during the heuristic's operation. However, *normalization* is much needed for conducting global comparisons across generations. Also, future work on surrogate-model building will necessitate some form of normalization (to be further discussed in Section 5.1). A standard form of normalization, using the two assayed references of a particular iteration (g), is the following:

$$f\left(\vec{\tau}^{(g)}\right) := \frac{\mathcal{L}_{i\to f}\left(\vec{\tau}^{(g)}\right) - \mathcal{L}_{i\to f}\left(\vec{\tau}_{\text{ih}}^{(g)}\right)}{\left(\mathcal{L}_{i\to f}\left(\vec{\tau}_0^{(g)}\right) - \mathcal{L}_{i\to f}\left(\vec{\tau}_{\text{ih}}^{(g)}\right)\right)}, \tag{6}$$

that is, setting a scale between the untreated "control" (being 1.0) and the "in-house protocol" (being 0.0). Another form of normalization, which accounts only for the "in-house protocol", reads:

$$\tilde{f}\left(\vec{\tau}^{(g)}\right) := \frac{\mathcal{L}_{i\to f}\left(\vec{\tau}^{(g)}\right) - \mathcal{L}_{i\to f}\left(\vec{\tau}_{\text{ih}}^{(g)}\right)}{\mathcal{L}_{i\to f}\left(\vec{\tau}_{\text{ih}}^{(g)}\right)}. \tag{7}$$

These formulae will be used in our presentation of the results.

4 EXPERIMENTAL OBSERVATIONS

Next, we describe in detail the experimental results that were obtained during the 7-iterations campaign over the two systems.

4.1 Presentation of Results

Figure 1 depicts the entire set of combinations that were evaluated on both systems. It introduces a hybrid *lollipop* visualization, exhibiting the raw function values (log-scaled) and the decision variables. Moreover, Figure 2 provides a gallery of photographs of the 20°C system (4^{th} generation) taken after 4 weeks of storage.

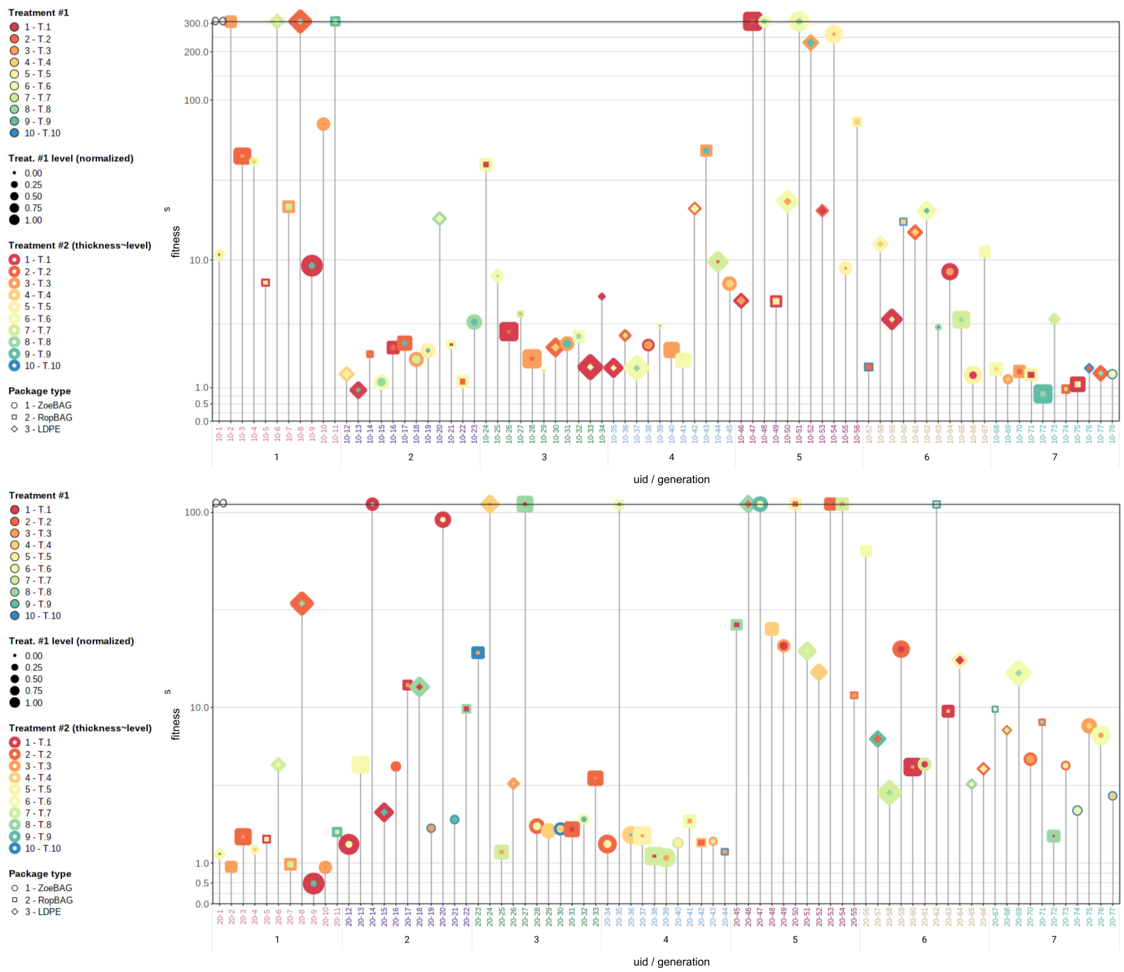

Figure 1: The objective function *raw* values of the entire campaign of the 10°C [TOP] and 20°C [BOTTOM] systems, encompassing 7 generations. The unnormalized objective function values are log-scaled. The current *lollipop* visualization depicts a hybrid of the raw function values and the decision variables. The glyph represents the packaging type, its dual color is defined by the first and second treatments, whereas their activation levels are represented by symbol size and border thickness.

Clearly, it is problematic to draw conclusions over the limited observation of 7 generations, especially when the cross-generational comparison of raw values is questionable. Therefore, in what follows, our analysis will examine the level of coverage of the categorical sub-space (Section 4.3), as well as the nature of the attained protocols (Section 4.4). Firstly, however, we report on the attempt to normalize the data.

4.2 Objective Function Values' Normalization

Table 1 presents the objective function values of the references in each generation. Clearly, high variance is observed for each reference per each system. This variance is likely rooted in seasonal differences, since the generations are practically spanned over several months, and the cucumbers' growing conditions vary.

By using these reference values, normalization was applied to the raw objective function values via (6) or (7), as long as the values of $\mathcal{L}_{i\to f}\left(\vec{\tau}_0^{(g)}\right)$, $\mathcal{L}_{i\to f}\left(\vec{\tau}_{\text{ih}}^{(g)}\right)$ were finite in generation g (i.e., both references ended up *unrotten*). Figure 3 presents these normalized values of the top 25% protocols (i.e., 75^{th}-percentile) across the two systems. Due to rotten references, the 1^{st} and the 5^{th} generations of the 10°C system, as well the 5^{th} generation of the 20°C system, are absent from this perspective. We examined the global rankings (i.e., following cross-generational sorting) among the entire sets of evaluated search-points. It is evident that the global rankings of the raw values are not consistent with the normalized values (that is, the rankings are not aligned; see Figure 3[TOP] for (6)), likely due to inter-generational variability of the reference values. However, when compared in this perspective, a trend of ascending values is observed along the ordering, suggesting that the rankings are correlated to some extent. We performed a statistical test to quantify this correlation and calculated Pearson's correlation coefficients (r-values) between the raw values to each of the two normalization forms. Notably, Pearson's r-values read $r_{(6)} = 0.48$ and $r_{(7)} = 0.55$ for the normalization forms (6) and (7), respectively. Indeed, these

Figure 2: Photography of the 4^{th} generation of the 20°C system after 4 weeks of storage. TOP LEFT: untreated fruit ("control"); TOP RIGHT: practiced protocol ("in-house"); BOTTOM LEFT: worst individual; BOTTOM RIGHT: best individual.

system	reference	$g=1$	$g=2$	$g=3$	$g=4$	$g=5$	$g=6$	$g=7$
10°C	$\vec{\tau}_0^{(g)}$	∞	∞	11.259	7.273	∞	4.506	2.443
	$\vec{\tau}_{\text{ih}}^{(g)}$	∞	5.411	3.894	1.485	6.667	2.048	0.790
20°C	$\vec{\tau}_0^{(g)}$	17.876	40.03	4.187	2.772	∞	107.128	15.836
	$\vec{\tau}_{\text{ih}}^{(g)}$	0.525	10.999	2.426	1.244	∞	3.090	1.436

Table 1: Explicit objective function values of the two references of every generation during the experimental campaign.

r-values reflect weak to moderate correlation. Overall, we conclude that applying normalization requires further investigation, since it does not provide satisfying outcome in its current form.

4.3 Coverage of the Categorical Sub-Space

We question the efficacy of the proposed algorithm in covering the sub-space of treatments and packaging, that is, the *exploration* capability of the sub-space of $\vec{d}$ within $\vec{\varphi}$ (5). This *categorical* sub-space comprises $10 \cdot 9 \cdot 3 = 270$ combinations altogether. An examination of the search-points visited by the algorithm reveals that this sub-space was well-covered considering the budget of 77 evaluations: there were 61 and 64 unique $\vec{d}$-points per the 10°C and 20°C systems, respectively, encompassing $\approx 23\%$ of the categorical sub-space (versus maximally attainable coverage of 28.5% by enumeration using this budget). Figure 4 visualizes this coverage of the categorical search-space by a 3D scatter plot per the 20°C system. This observation indicates that the employed ES is highly exploratory during the first generations, as expected from this class of heuristics in the early stage of evolution. It may also serve as a validation for the effective application of the self-adaptive mutation and the recombination operators in the context of exploration.

4.4 Nature of Attained Solutions

Figure 5 shows the top 6 protocols obtained by the entire campaign of the 20°C system, using spider charts to visualize the decision variables. The spider charts of the 10°C system are excluded due to space limitations. We will describe the nature of the attained solutions of both systems, without going into postharvest details (the scientific analysis of the explicit treatments exceeds the scope of this paper). The top-ranked protocols are explainable by the postharvest experts, although some combinations of treatments possess a surprising nature. Also, the fact that the 3 packaging types appear in the top-ranked protocols (10°C only; data was not shown) is also surprising, especially the LDPE type (which is composed of the cheapest polymer, rendering its associated protocol an attractive candidate according to the yet unexplored economical aspect).

5 DISCUSSION AND SUMMARY

The current study introduced the postharvest quality loss minimization problem, and formulated it as an experimental combinatorial single-objective optimization problem (3) over the search-space of treatment protocols (1). Such a generalized perspective, when applied to cucumbers with commonly exercised postharvest practices (10 treatments and 3 packaging types), resulted in a vast search-space of 10^{17} possible combinations. Then, by adhering to pragmatic settings in common postharvest laboratories, and by accounting for realistic settings in future real-world deployment of such protocols, we considered a constrained model using only 2 treatments prior to the packaging phase (4), which reduced the search-space cardinality to $\sim 10^6$. We presented a compact form for this model using the 5-dimensional $\vec{\varphi}$ representation (5), and proposed an ES to address it (with its kernel being Algorithm 1).

Evidently, the proposed heuristic obtained satisfying results by locating a diverse set of protocols, which outperform the best known practices, including some protocols with a surprising nature that will necessitate fundamental postharvest research. Furthermore, protocols that proved successful upon evaluations (post-4-weeks), were placed back in storage for an extended period of time (9 weeks altogether). Figure 6 presents a gallery of the 3^{rd} generation, whose best individual was kept in storage for an overall period of 9 weeks. The fruit exhibited a surprising postharvest quality, while the two references ended up completely rotten (photography is excluded). To the best of our knowledge, such a postharvest accomplishment for cucumbers has not been reported yet in the literature.

Two versions of normalization were applied to the objective function values, in order to render them comparable across generations. These attempts were only partially successful, and will require additional research efforts. The generational gaps within raw fitness values are reflected by the high variance of the measured references ("untreated" and "in-house"), which were explicitly analyzed. The high variance may be explained by the fact that exogenous growing factors have varied during the course of this experimental campaign. In that sense, the optimization problem could be considered to possess a *dynamic* objective function. Nevertheless and importantly, the lack of normalization did not hamper the search, which relied only on per-generation rankings. It will affect, though, future attempts to accomplish learning of the response surfaces.

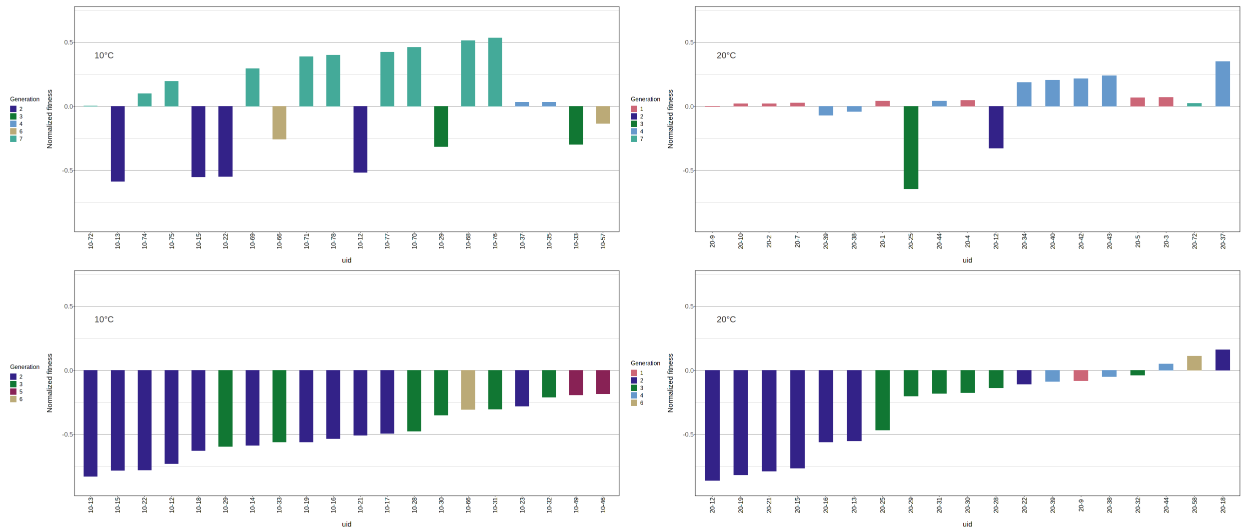

Figure 3: The normalized objective function values of the protocols of the 75^{th}-percentile: the $10°$C [LEFT] and $20°$C [RIGHT] systems. This *bar* visualization depicts the ordered protocols (best at the left-most position; colored according to generation), whereas negative bars represent protocols that outperform the "in-house protocol" $\vec{\tau}_{\mathbf{ih}}$.
TOP: Normalization using (6) and ordering according to the raw values. The global rankings of the raw values are not consistent with the normalized values, likely due to inter-generational variability of the reference values. However, a trend of ascending values is observed, suggesting that the rankings are weakly correlated. BOTTOM: Normalization using (7) and ordering according to the normalized values. Within this context, generation 2 produced the best protocols in both systems.

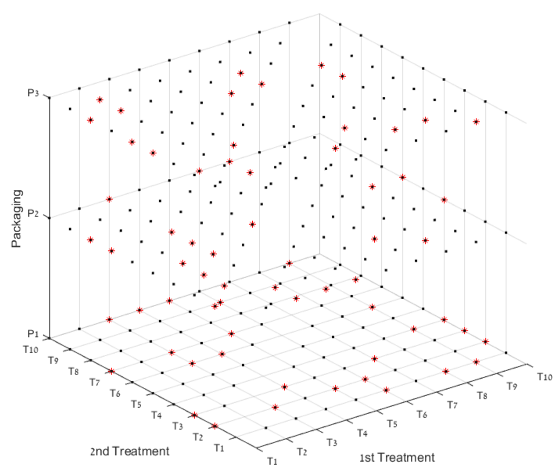

Figure 4: The categorical sub-space visualized by a 3D scatter plot, depicting all the 270 feasible search-points (black points), and those visited *de facto* by the algorithm per the $20°$C system (64 red stars). Importantly, the Tabu restriction within the mutation operator is applied to the entire 5-dimensional decision vector, allowing the algorithm to revisit the same categorical combinations while searching the integer activation levels. The observed coverage of this categorical sub-space is indicative of the high exploratory nature of the employed ES.

5.1 Generalization and Future Work

We outline some potent directions for future research:

(1) Learning the *postharvest response surface* is a highly attractive research pathway, whose merit is twofold: (i) surrogate-model construction, and (ii) postharvest mechanistic investigation. Firstly, utilization of surrogate-models (also known as metamodeling; see, e.g., [7, 8, 31]) would serve as a practical accelerator for the sequential experimentation process. Secondly, obtaining response-surfaces of color/stiffness/mass deviations would contribute to unveiling postharvest mechanisms, which constitutes a grand fundamental research challenge.

(2) Multiobjective Optimization (see, e.g., [41]) is a natural algorithmic extension. The idea would be to replace the aggregation of $\mathcal{L}_{i\to f}\left(\vec{\tau}\right)$ in (3) by a vectorized, quad-criteria Pareto approach:

$$\begin{aligned} &\Delta c\left(\vec{\tau}\right) \mapsto \min, \\ &\Delta s\left(\vec{\tau}\right) \mapsto \min, \\ &\Delta m\left(\vec{\tau}\right) \mapsto \min, \\ &\text{score}_{\text{exp}}\left(\vec{\tau}\right) \mapsto \min\ . \end{aligned} \tag{8}$$

While this direction is expected to introduce high demands concerning the experimental budget, it would be possible to capitalize on dedicated multiobjective approaches for expensive evaluations [19, 20]. In addition, constructing the aforementioned surrogate-models would facilitate such extended setups.

(3) A possible research question could target "optima transfer". From a postharvest point of view, it is highly relevant to

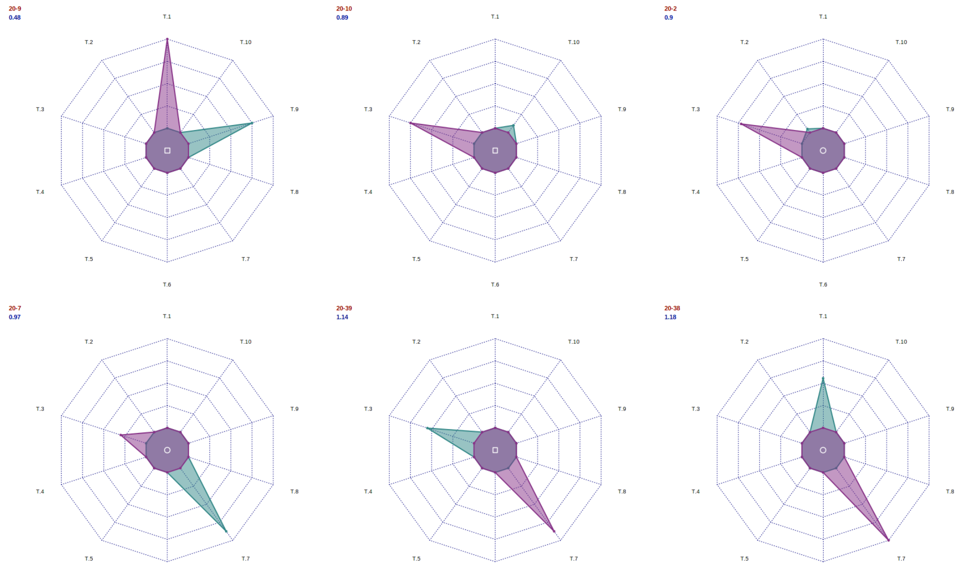

Figure 5: The top 6 protocols obtained by the entire campaign of the 20°C system. The current *spider* visualization depicts the decision variables. The first and second treatments are marked by the inner colored pointers (green for the 1^{st} and purple for the 2^{nd}), and their activation levels are represented by the pointers' magnitudes. The packaging type is marked in its center: *diamond* for LDPE, *square* for RopBAG, *circle* for ZoeBAG.

Figure 6: The 3^{rd} generation of the 20°C system after 4 and 9 weeks of storage. TOP LEFT: untreated fruit ("control") post-4-weeks; TOP RIGHT: practiced protocol ("in-house") post-4-weeks; BOTTOM LEFT: best individual post-4-weeks; BOTTOM RIGHT: best individual post-9-weeks.

question the applicability of the attained protocols to other family members (*Cucurbitaceae*), e.g., the zucchini.

(4) One-Shot Optimization [1] is a promising direction to address the postharvest search challenge of crops that feature a limited time-window for experimentation – e.g., berries. Conducting sequential experimentation campaigns, of the nature reported herein, may be infeasible in such cases, whereas one-shot optimization may prove successful.

5.2 Impact and Outlook

Indeed, the sequential experimentation perspective is not novel from the algorithmic point of view, since it is deeply rooted in the Evolutionary Computation field (noted earlier in the Introduction). In the future, as more experiments will be algorithmically-guided analogously to the reported experiments herein, the roles of the scientists/engineers will shift from locating solutions/designs to explaining the nature of the attained results while aiming for mechanistic understanding. The application of the proposed approach to minimize quality loss of fresh products is of great interest to the Agro/Food industries, whose roadmap encompasses the automation of processes combined with the integration of AI capabilities. The ability to automatically reproduce scientific results, by extracting knowledge from scientific literature, has been accomplished in the domain of chemical syntheses [23]. With the AI revolution taking place, we question whether more decisions in scientific experiments may be driven by the machine. In particular, we foresee the formulation of scientific hypotheses as the possible next leap-frog of AI, capitalizing on established knowledge representation frameworks [15], and machine-driven causal inference [29].

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REFERENCES

[1] Jakob Bossek, Carola Doerr, Pascal Kerschke, Aneta Neumann, and Frank Neumann. 2020. Evolving Sampling Strategies for One-Shot Optimization Tasks. In *Parallel Problem Solving from Nature – PPSN XVI (PPSN 2020) (Lecture Notes in Computer Science, Vol. 12269)*. Springer, Leiden, Netherlands, 111–124. https://doi.org/10.1007/978-3-030-58112-1_8

[2] George E.P. Box, J. Stuart Hunter, and William G. Hunter. 2005. *Statistics for Experimenters: Design, Innovation and Discovery* (second ed.). John Wiley and Sons, Hoboken, NJ, USA.

[3] Ozgul Calicioglu, Alessandro Flammini, Stefania Bracco, Lorenzo Bellù, and Ralph Sims. 2019. The future challenges of food and agriculture: An integrated analysis of trends and solutions. *Sustainability (Switzerland)* 11, 1 (2019). https://doi.org/10.3390/su11010222

[4] Diego Calzolari, Stefania Bruschi, Laurence Coquin, Jennifer Schofield, Jacob D. Feala, John C. Reed, Andrew D. McCulloch, and Giovanni Paternostro. 2008. Search Algorithms as a Framework for the Optimization of Drug Combinations. *PLoS Computational Biology* 4, 12 (Dec. 2008), e1000249.

[5] Bingxia Chen and Huqing Yang. 2013. 6-Benzylaminopurine alleviates chilling injury of postharvest cucumber fruit through modulating antioxidant system and energy status. *Journal of the Science of Food and Agriculture* 93, 8 (2013), 1915–1921. https://doi.org/10.1002/jsfa.5990

[6] Indraneel Das and John Dennis. 1997. A closer look at drawbacks of minimizing weighted sums of objectives for Pareto set generation in multucriteria optimization problems. *Structural Optimization* 14 (1997), 63–69.

[7] M.A. El-Beltagy, P.B. Nair, and A.J. Keane. 1999. Metamodelling Techniques for Evolutionary Optimisation of Computationally Expensive Problems: Promises and Limitations. In *Proceedings of the Genetic and Evolutionary Computation Conference, GECCO-1999*, W. Banzhaf, J. Daida, A.E. Eiben, M.H. Garzon, V. Honavar, M. Jakiela, and R.E. Smith (Eds.). Morgan Kaufman, 196–203.

[8] Michael Emmerich, Alexios Giotis, Mutlu Özdemir, Thomas Bäck, and Kyriakos Giannakoglou. 2002. Metamodel-Assisted Evolution Strategies. In *Parallel Problem Solving from Nature - PPSN VII (Lecture Notes in Computer Science, Vol. 2439)*. Springer, Berlin, 361–370.

[9] Chen Erlich. 2019. *Experimental Combinatorial Optimization of Phycobiliproteins' Expression in E. Coli.* Master's thesis. Tel-Hai College.

[10] Christian Fikar and Kris Braekers. 2022. Bi-objective optimization of e-grocery deliveries considering food quality losses. *Computers and Industrial Engineering* 163 (2022), 107848. https://doi.org/10.1016/j.cie.2021.107848

[11] Food and Agriculture Organization of the United Nations. 2018. *The future of food and agriculture – Alternative pathways to 2050.* 224 pages.

[12] R. García-Flores, O.V. de Souza Filho, R.S. Martins, C.V.B. Martins, and P. Juliano. 2015. 11 - Using logistic models to optimize the food supply chain. In *Modeling Food Processing Operations*, Serafim Bakalis, Kai Knoerzer, and Peter J. Fryer (Eds.). Woodhead Publishing, 307–330. https://doi.org/10.1016/B978-1-78242-284-6.00011-8

[13] Mahmood Ul Hasan, Rana Naveed Ur Rehman, Aman Ullah Malik, Muhammad Wasim Haider, Zeeshan Ahmed, Ahmad Sattar Khan, and Raheel Anwar. 2020. Pre-storage Application of L-arginine Alleviates Chilling Injury and Maintains Postharvest Quality of Cucumber (Cucumis sativus). *Journal of Horticultural Science and Technology* March 2020 (2020), 102–108. https://doi.org/10.46653/jhst190204102

[14] Naama Horesh, Thomas Bäck, and Ofer M. Shir. 2019. Predict or screen your expensive assay? DoE vs. surrogates in experimental combinatorial optimization. In *Proceedings of the Genetic and Evolutionary Computation Conference, GECCO 2019, Prague, Czech Republic, July 13-17, 2019.* 274–284. https://doi.org/10.1145/3321707.3321801

[15] Anthony Hunter and Weiru Liu. 2010. A survey of formalisms for representing and reasoning with scientific knowledge. *Knowl. Eng. Rev.* 25, 2 (2010), 199–222. https://doi.org/10.1017/S0269888910000019

[16] Ibrahim Kahramanoğlu and Serhat Usanmaz. 2019. Improving postharvest storage quality of cucumber fruit by modified atmosphere packaging and biomaterials. *HortScience* 54, 11 (2019), 2005–2014. https://doi.org/10.21273/HORTSCI14461-19

[17] M. Ufuk Kasim and Rezzan Kasim. 2008. UV-A treatment delays yellowing of cucumber during storage. *Journal of Food, Agriculture and Environment* 6, 2 (2008), 29–32.

[18] Douglas B. Kell. 2012. Scientific discovery as a combinatorial optimisation problem: How best to navigate the landscape of possible experiments? *BioEssays* 34, 3 (2012), 236–244. https://doi.org/10.1002/bies.201100144

[19] Joshua Knowles. 2006. ParEGO: A Hybrid Algorithm with On-Line Landscape Approximation for Expensive Multiobjective Optimization Problems. *IEEE Transactions on Evolutionary Computation* 10, 1 (January 2006), 50–66.

[20] Joshua Knowles, David Corne, and Alan Reynolds. 2009. Noisy Multiobjective Optimization on a Budget of 250 Evaluations. In *EMO '09: Proceedings of the 5th International Conference on Evolutionary Multi-Criterion Optimization* (Nantes, France). Springer-Verlag, Berlin, Heidelberg, 36–50. https://doi.org/10.1007/978-3-642-01020-0_8

[21] P. V. Mahajan, O. J. Caleb, Z. Singh, C. B. Watkins, and M. Geyer. 2014. Postharvest treatments of fresh produce. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 372, 2017 (2014), 20130309. https://doi.org/10.1098/rsta.2013.0309

[22] M. Manjunatha and Rahul K. Anurag. 2014. Effect of modified atmosphere packaging and storage conditions on quality characteristics of cucumber. *Journal of Food Science and Technology* 51, 11 (2014), 3470–3475. https://doi.org/10.1007/s13197-012-0840-7

[23] S. Hessam M. Mehr, Matthew Craven, Artem I. Leonov, Graham Keenan, and Leroy Cronin. 2020. A universal system for digitization and automatic execution of the chemical synthesis literature. *Science* 370, 6512 (2020), 101–108. https://doi.org/10.1126/science.abc2986

[24] Dagmara Migut, Józef Gorzelany, Piotr Antos, and Maciej Balawejder. 2019. Postharvest Ozone Treatment of Cucumber as a Method for Prolonging the Suitability of the Fruit for Processing. *Ozone: Science and Engineering* 41, 3 (2019), 261–264. https://doi.org/10.1080/01919512.2018.1525277

[25] Ibrahim N. Nasef. 2018. Short hot water as safe treatment induces chilling tolerance and antioxidant enzymes, prevents decay and maintains quality of cold-stored cucumbers. *Postharvest Biology and Technology* 138, December 2017 (2018), 1–10. https://doi.org/10.1016/j.postharvbio.2017.12.005

[26] Torsten Nilsson. 2005. Effects of ethylene and 1-MCP on ripening and senescence of European seedless cucumbers. *Postharvest Biology and Technology* 36, 2 (2005), 113–125. https://doi.org/10.1016/j.postharvbio.2004.11.008

[27] Abiola Owoyemi, Ron Porat, and Victor Rodov. 2021. Effects of compostable packaging and perforation rates on cucumber quality during extended shelf life and simulated farm-to-fork supply-chain conditions. *Foods* 10, 2 (2021), 1–14. https://doi.org/10.3390/foods10020471

[28] Charmi Patel and Jitendriya Panigrahi. 2019. Starch glucose coating-induced postharvest shelf-life extension of cucumber. *Food Chemistry* 288, February (2019), 208–214. https://doi.org/10.1016/j.foodchem.2019.02.123

[29] Judea Pearl. 2019. The Seven Tools of Causal Inference, with Reflections on Machine Learning. *Commun. ACM* 62, 3 (feb 2019), 54–60. https://doi.org/10.1145/3241036

[30] Herschel Rabitz, Re-Bing Wu, Tak-San Ho, Katharine Moore Tibbetts, and Xiaojiang Feng. 2014. *Fundamental Principles of Control Landscapes with Applications to Quantum Mechanics, Chemistry and Evolution.* Springer Berlin Heidelberg, Berlin, Heidelberg, 33–70. https://doi.org/10.1007/978-3-642-41888-4_2

[31] A. Ratle. 1998. Accelerating the Convergence of Evolutionary Algorithms by Fitness Landscape Approximations. In *Parallel Problem Solving by Nature - PPSN V (Lecture Notes in Computer Science)*. Springer-Verlag, Berlin, 87–96.

[32] Edgar Reehuis and Thomas Bäck. 2010. Mixed-integer evolution strategy using multiobjective selection applied to warehouse design optimization. In *Proceedings of the 12th annual conference on Genetic and evolutionary computation* (Portland, Oregon, USA) *(GECCO '10)*. ACM, New York, NY, USA, 1187–1194. https://doi.org/10.1145/1830483.1830700

[33] Günter Rudolph. 2012. *Handbook of Natural Computing: Theory, Experiments, and Applications*. Springer-Verlag, Berlin-Heidelberg, Germany, Chapter Evolutionary Strategies, 673–698.

[34] Hans-Paul Schwefel. 1995. *Evolution and Optimum Seeking*. John Wiley & Sons, Inc., New York, NY, USA.

[35] Nan Shan, Zengyu Gan, Jing Nie, Huan Liu, Zhenyu Wang, and Xiaolei Sui. 2020. Comprehensive Characterization of Fruit Volatiles and Nutritional Quality of Three Cucumber (Cucumis sativus L.) Genotypes from Different Geographic Groups after Bagging Treatment. *Foods* 9, 3 (2020). https://doi.org/10.3390/foods9030294

[36] Ofer M. Shir and Thomas Bäck. 2021. Sequential Experimentation by Evolutionary Algorithms. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion* (Lille, France) *(GECCO '21)*. Association for Computing Machinery, New York, NY, USA, 941–958. https://doi.org/10.1145/3449726.3461410

[37] Edward S. Spang, Laura C. Moreno, Sara A. Pace, Yigal Achmon, Irwin Donis-Gonzalez, Wendi A. Gosliner, Madison P. Jablonski-Sheffield, Md Abdul Momin, Tom E. Quested, Kiara S. Winans, and Thomas P. Tomich. 2019. Food Loss and Waste: Measurement, Drivers, and Solutions. *Annual Review of Environment and Resources* 44 (2019), 117–156. https://doi.org/10.1146/annurev-environ-101718-033228

[38] USDA. 2018. United States Standards for Grades of Cucumbers. *Marketing and Regulatory Programs* (2018).

[39] Chien Yi Wang and Douglas O. Adams. 1982. Chilling-Induced Ethylene Production in Cucumbers (Cucumis sativus L.) . *Plant Physiology* 69, 2 (1982), 424–427. https://doi.org/10.1104/pp.69.2.424

[40] Dirk Weuster-Botz and Christian Wandrey. 1995. Medium optimization by genetic algorithm for continuous production of formate dehydrogenase. *Process Biochemistry* 30, 6 (1995), 563–571.

[41] Eckart Zitzler. 2012. *Handbook of Natural Computing: Theory, Experiments, and Applications.* Springer-Verlag, Berlin-Heidelberg, Germany, Chapter Evolutionary Multiobjective Optimization, 871–904.