Improving Greenhouse Environmental Control Using Crop-Model-Driven Multi-Objective Optimization

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ABSTRACT

Optimal control of greenhouse environments can be improved by using a combined microclimate-crop-yield model to allow selection of greenhouse designs and control algorithms to maximize the profit margin. However, classical methods for optimal greenhouse control are not adequate to establish the tradeoffs between multiple objectives. We use NSGA-II to evolve the setpoints for microclimate control in a greenhouse simulation and define two objectives: minimizing variable costs and maximizing the value of the tomato crop yield. Results show that the evolved setpoints can provide the grower a variety of better solutions, resulting in greater profitability compared to prior simulated results. The Pareto front also provides additional information to the grower, showing the economic tradeoffs between variable costs and tomato crop yield, which can aid in decision making.

CCS CONCEPTS

• **Applied computing~Environmental sciences** • Applied computing~Multi-criterion optimization and decision-making

KEYWORDS

Multi-objective evolutionary optimization, greenhouse control

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1 INTRODUCTION

Prior work [3-4] on this application shows the promise of treating greenhouse control as a multi-objective problem, but many economic parameters are required for a grower to make a well-informed, financially sound decision. Further, while the primary goals of the grower are to maximize yield and minimize energy costs, compromises are needed due to the conflicting nature of these goals. Rather than incorporating these goals into a single objective or as constraints, they can instead be added as additional objectives in a multi-objective evolutionary algorithm, in this case NSGA-II [1].

Vanthoor [2] proposed a model-based greenhouse design methodology that includes an economic model to determine the financial viability of a variety of greenhouse designs under climates in Southern Spain. Although his results show that this methodology is effective at optimizing greenhouse designs, optimization of climate control setpoints was beyond the scope of that study, although genetic algorithms were mentioned as a potential solution for this type of optimization problem.

2 OPTIMIZATION METHODOLOGY

All the parameters required to describe the characteristics of the greenhouse design and climate control, including the economic parameters associated with them were obtained from Vanthoor's greenhouse case study in Almería, Spain [2], therefore a tomato crop is assumed for the output yield. Fig. 1 describes the optimization methodology used, including the changes we introduced.

The economic model's primary goal is to calculate the annual net financial result (NFR), and is defined as:

$$Q_{NFR}(t_f) = -Q_{Fixed} + \int_{t=t_0}^{t=t_f} \dot{Q}_{CropYield} - \dot{Q}_{Var}\, dt$$

where $Q_{CropYield}$ (€×m^{-2}×year^{-1}) is the value of the tomato crop, Q_{Var} (€×m^{-2}×year^{-1}) consists of the variable costs (costs associated with the crop, resources used and labor), and Q_{Fixed} (€×m^{-2}×year^{-1}) represents the cost of all tangible assets that do not depend on crop growth. By using the terms inside the integral, we can then establish the desired objectives: minimizing Q_{Var} and maximizing $Q_{CropYield}$.

The simulation uses a weather prediction model as input, and three weather seasons are evaluated for each individual, with the fitness function choosing the season with the worst NFR. This incurs an added computational cost but allows us to define a more conservative strategy that aims to minimize the losses during the worst seasons while ensuring the evolved setpoints can perform well under multiple weather seasons. Table 1 contains a summary of the relevant simulation parameters.

Table 1: Simulation parameters. "WHFC" denotes the use of whitewash (W), a boiler heating system (H), a fogging system (F) and a CO_2 enrichment system.

Parameter	Value
Growing periods	August 1st, 2006 – July 1st, 2007
	August 1st, 2007 – July 1st, 2008
	August 1st, 2008 – July 1st, 2009
Simulation Length	334 days
Coordinates	36°48'N, 2°43'W
Height above sea level	151 meters
Greenhouse design	WHFC

The chromosome represents the setpoints at which various greenhouse climate control actuators are turned on or off and remain fixed once the simulation begins.

3 RESULTS AND DISCUSSION

The Pareto front in Fig. 2 is compared with the original setpoints of a classical control strategy [2]. The original is clearly not Pareto optimal, despite not being dominated by many evolved setpoints. In addition, Table 2 shows that even if a new set of weather data (2009 – 2010) is used, we can find evolved setpoints that outperform the original setpoints in terms of NFR.

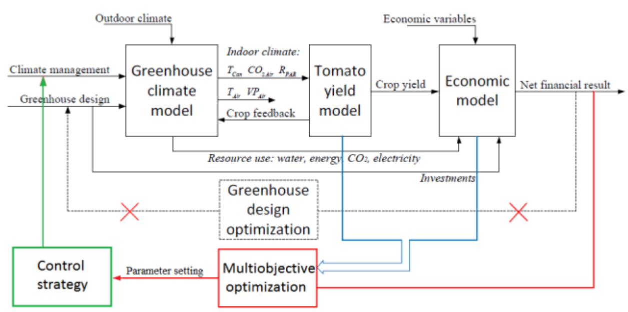

Figure 1: Overview of Vanthoor's method [2], modified for control setpoint optimization. Microclimate state variables are used as input for the tomato yield model, such as canopy temperature (T_{Can}), photosynthetically active radiation flux density (R_{PAR}), greenhouse air temperature (T_{Air}) and greenhouse air vapor pressure (VP_{Air}).

4 CONCLUSIONS AND FUTURE WORK

We showed that multi-objective evolutionary algorithms like NSGA-II can be used to aid the grower in the design stages of greenhouse construction by optimizing the control setpoints. In addition, these setpoints can be evolved between growing seasons as new data are available and as input costs change. We found evolved control setpoints that outperform the original setpoints in two objectives: maximizing the economic value of the crop yield and minimizing the variable costs, even when using a new set of weather data that was not used during the evolutionary optimization process. Future work will focus on evolving more complex control strategies on a wider range of time periods and locations.

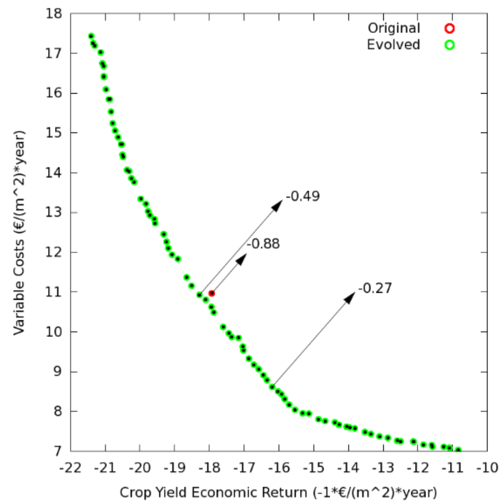

Figure 2: Pareto front consisting of the evolved control setpoints compared against the original control setpoints. The worst-case net financial results of the original setpoint and two evolved setpoints are shown.

Table 2: Economic model output (€×m^{-2}×year^{-1}), comparing the original setpoints vs a "low-cost" solution and a "high-value" solution obtained from the Pareto front in Fig. 2. Net financial results (NFR) for all four years are added up.

	Original			Low Cost			High Value		
Period	**Crop Value**	**Var. Costs**	**NFR**	**Crop Value**	**Var. Costs**	**NFR**	**Crop Value**	**Var. Costs**	**NFR**
'06 - '07	19.03	10.98	0.19	17.29	8.65	0.79	19.39	10.88	0.66
'07 - '08	20.69	11.41	1.44	18.72	9.11	1.76	21.10	11.42	1.83
'08 - '09	17.95	10.97	-0.88	16.20	8.62	-0.27	18.29	10.93	-0.49
'09 - '10	18.90	10.96	0.09	17.23	8.76	0.62	19.29	10.95	0.49
Total			**0.85**			**2.91**			**2.49**

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