CSE/ECE 848 Introduction to Evolutionary Computation

Module 5, Lecture 22, Part 2a
Evolutionary Multi-Objective Optimization for Greenhouse Control

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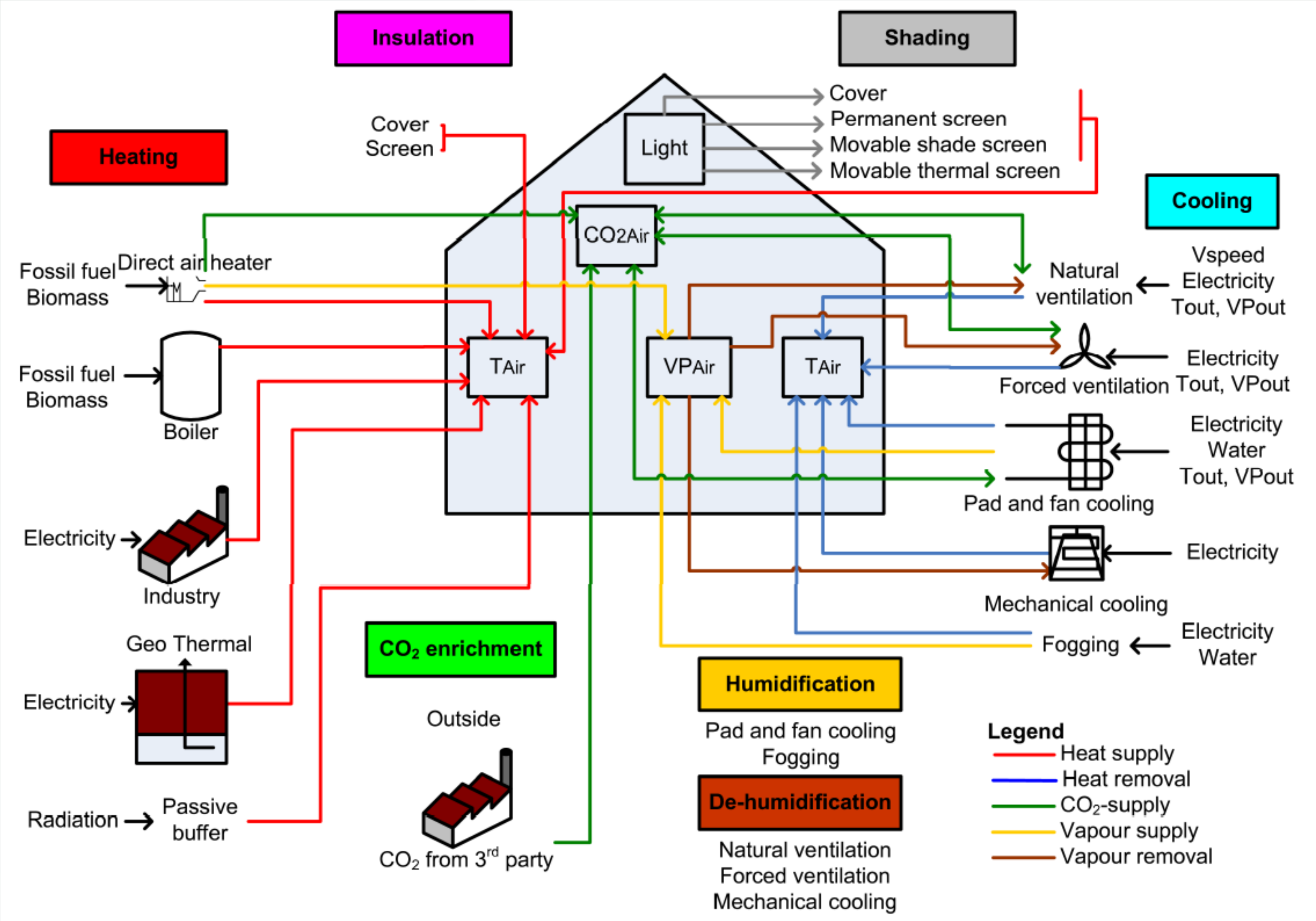
This example is based on the doctoral dissertation research of my former Ph.D. student, Dr. José Llera-Ortiz

- He defended in August, 2020
- He is now at the Applied Physics Laboratory, Johns Hopkins University
- The greenhouse model and tomato growth model underlying the work was based on models developed by Bram Vanthoor, published in 2011 (Ph.D. Dissertation, Wageningen University)

Vanthoor's Model

- Proposed a generic model-based optimization method
- Complete mechanistic model
  - Climate, crop yield, economic models
  - Aimed at making greenhouse ***design*** decisions, not optimizing controls
- Control actions based on current practice-- Did not optimize the controller actions as a function of actual weather conditions, crop state, etc.

Vanthoor's Model

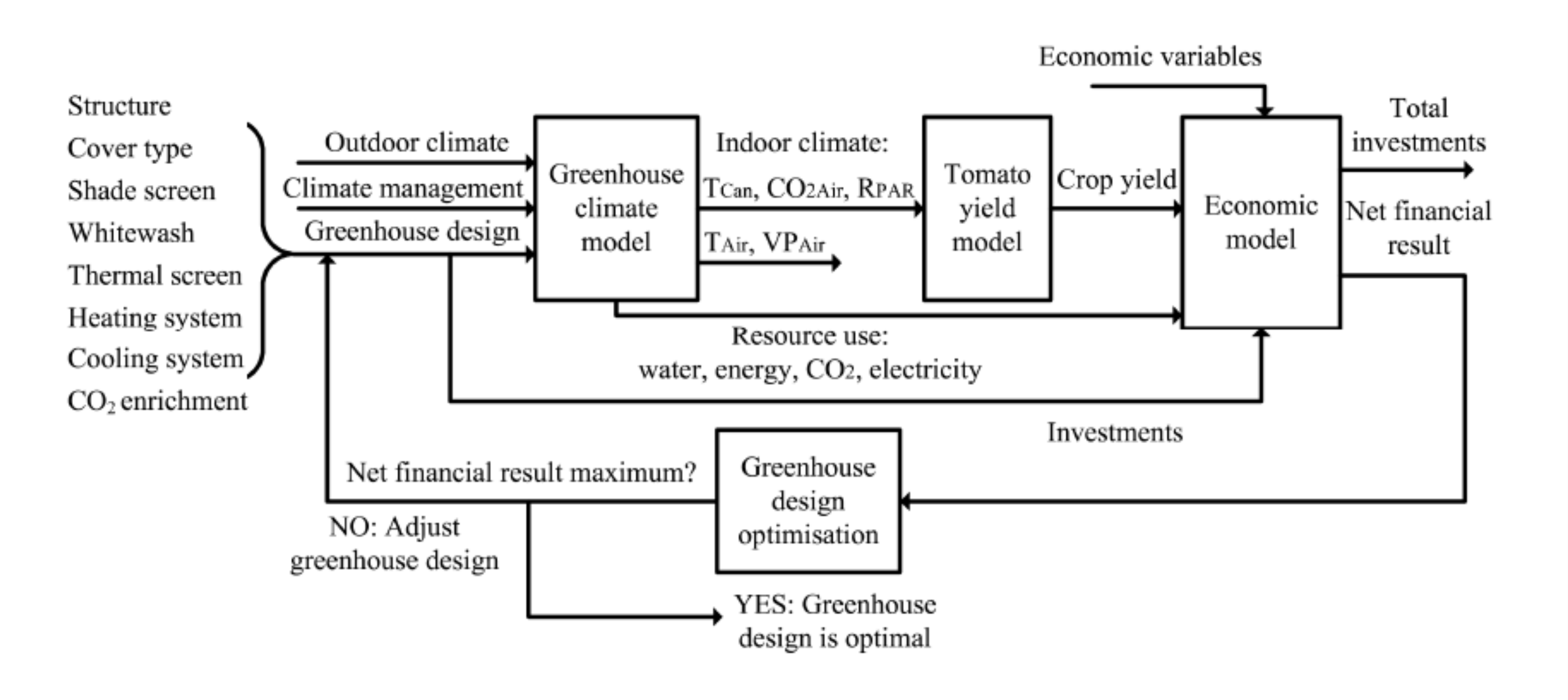


Source: Vanthoor, 2011

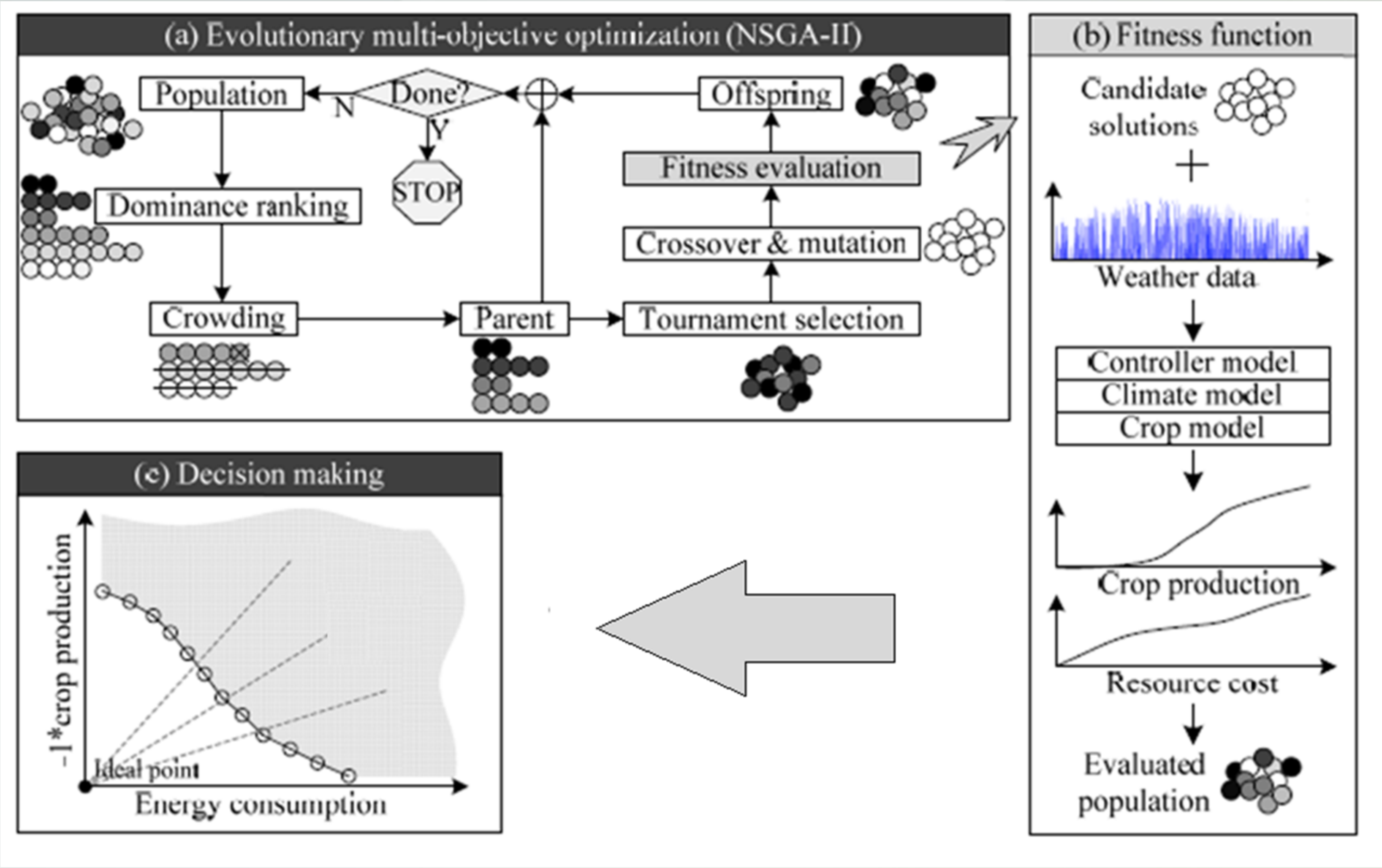
Vanthoor's Model

Source: Vanthoor, 2011

- Dynamic design methodology
- Static control strategy
- Single objective—
  Net Financial Result (NFR)



Multi-Objective Optimization Introduced, using NSGA-II



Model Modifications to Evolve Controllers

Challenges

- Combined model is computationally expensive
  - “Stiff” differential equations require tiny timesteps
- For MOEAs optimizing controllers to be feasible, faster run times are essential

Solution

- Reduced number of state variables, validated that behavior almost unchanged
- Still used a variable timestep ODE solver, but new model simulates much faster

The Reduced Model:

- Unnecessary greenhouse design elements are omitted
  - We're not evolving the greenhouse design features, just the controller
- Greenhouse design is fixed
  - Enough design elements for complex control strategies
  - Output can be compared with results in literature
  - Could evaluate 8,000 controllers in 24 hours in an HPCC using 40 cores

NSGA-II Parameters

- Population size and generations based on available resources
- Mutation probability based on size *N* of a chromosome

Parameter	Value
Population size	80
Generations	100
Two-point crossover probability	0.3
Uniform mutation probability	1/N

Chromosome Definition

- Chromosome values stored as **integer** vector – WHY INTEGERS?
- Size = 9 integers
- 1.045×10^{26} distinct chromosomes

Parameter	Range	Step Size
$T_{AirVentOn}$ (°C)	[10, 30]	0.1
$T_{AirVentOff}$ (°C)	[10, 30]	0.1
$RH_{AirVentOn}$	[1, 10]/10.	0.01
$CO_{2AirVentOn}$ (ppm)	[100, 500]	0.1
$T_{AirBoilOn}$ (°C)	[10, 30]	0.1
$T_{OutThScrOn}$ (°C)	[10, 30]	0.1
$CO_{2AirExtMax}$ (ppm)	[500, 1000]	0.1
$CO_{2AirExtMin}$ (ppm)	[100, 500]	0.1
$I_{GlobMax}$ ($W \times m^{-2}$)	[200, 1000]	0.1

Evolved Control Strategies

- Controllers are evolved based on a classical strategy for selection of control parameters
  - More complex controllers can reproduce simpler behavior if needed