Co-simulation and Crop Representation for Digital Twins of Controlled Environment Agriculture Systems

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ABSTRACT

Cyber-biophysical systems are complex systems coupling a cyber-physical system to a biological entity. Such systems require the collaboration of multiple domain experts for their operation, which relies more on tacit knowledge than known optimal actions. Digital twins of cyber-biophysical systems provide a tool for operators to analyze and understand the complex behavior of their systems. However, digital twins must incorporate simulation and visualization services to represent the system, a vertical farm, in the case of controlled environment agriculture. To enable the operationalization of a vertical farm digital twin, we provide an overview of simulation and visualization services that enable the representation of multiple system concerns.

CCS CONCEPTS

• **Computing methodologies → Modeling methodologies**; *Discrete-event simulation*; *Continuous simulation*; *Scientific visualization*.

KEYWORDS

digital twins, cyber-biophysical systems, co-simulation, model transformation, controlled environment agriculture

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1 RESEARCH PROBLEM AND MOTIVATION

The digitization of many domains such as manufacturing [18], avionics [21], and logistics [9] has made the presence of cyber-physical systems ubiquitous. In agriculture, digitization has the potential to bring forth the most impact through smart farming technologies [3], such as vertical farming, a type of controlled environment agriculture (CEA). However, the operation of CEA systems is difficult due to the complexity of their constituent parts, especially the crops. Operators such as agronomists and growers typically rely on tacit experience to analyze the behavior of the system and operate it. By leveraging recent advances in digitization, namely digital twins, we aim to provide a tool for CEA system operators to maximize the crop yield while minimizing the energy cost of the system.

Digital twins model complex systems via a real-time connection between the physical system and its virtual counterpart, which, coupled with simulation, enables services such as what-if analyses and advanced visualizations. Those services allow operators to find optimal configurations of the system in terms of complex key performance indicators (KPI). However, the biological entities interact with ther environment in ways that are not fully understood, such as the impact of crop evapotranspiration on the HVAC system, and requires modeling the causal relationships between the crop and the environment to estimate energy loads.Further, digital twin users such as the agronomist and grower require domain-specific visualisations that represent different system concerns, such as the phenology and morphology of the crop. However, such models are typically built in silos and do not present consistent views.

To enable the simulation of complex KPI and the representation of multiple system concerns, we propose a simulation architecture for digital twins in smart agriculture that captures the interactions between the crop and the environment. Our approach couples co-simulation with a multi-objective optimization-based model transformation to represent various concerns of crop development. This article is part of an ongoing project towards the development and operationalization of a controlled environment agriculture digital twin in collaboration with our industrial partner d'Hiver [1]. The work in this manuscripts attempts to address challenges faced in early stages of the project [4, 8], and further work is required to address the control capabilities of CEA digital twins.

In the following sections, we detail the complexities incurred by our agricultural domain and provide our proposed solution and early results.

2 BACKGROUND AND RELATED WORKS

2.1 Digital twins in agriculture

Digital twins have demonstrated their potential to aid decision-makers with farm operations but have yet to be fully operationalized due to the complexities involving crop-environment dynamics [16]. Due to the rapid evolution and adoption of digital twins in many domains, much seminal work on digital twins focused on the development of *Monitoring Digital Twins*, a term taken from recent work on conceptual frameworks for digital in smart farming [22]. We plan to build upon those frameworks and detail what approach should be taken to develop an operational smart farming digital that goes beyond a monitoring use case and can provide recommendations for the optimal control of the system.

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2.2 Crop phenology and morphology

To provide actionable feedback, the digital twin must represent the concerns of crop phenological and morphological development to its users. Crop phenology captures the underlying dynamics of crop growth in relation to its environment. Typically, such models comprise modules for the computation of photosynthetic activity, soil nutrient exchange, evapotranspiration, and farming operations affecting the crop. These models are used by agronomists to predict the impact of environmental recipes on phenological crop attributes such as the weight of organs, the distribution of chemicals within the crop, and water evapotranspired.

In contrast, crop morphology defines the architectural and structural development of the crop and includes functions such as branching patterns and organ size and shape. Models of crop morphology capture the topology and relations between crop organs and include cultivar-specific parameters, such as branch angle or reproduction thresholds, to model organogenesis and branching patterns. Using the L-System formalism, morphological models embed biological well-formedness into their design to create accurate depictions of crops that yield actionable results to the agronomist and grower.

2.3 L-System & Turtle Graphics

The L-system formalism [26] was invented to simulate crop morphological development and model the growth processes of biological organisms. The formalism provides a framework for describing complex development patterns through the use of formal grammars and iterative, parallel rewriting rules acting upon a string. A string generated by the L-System is then interpreted visually through turtle graphics, sequentially drawing symbols by iterating over it. In this paper, we assume that L-system models enforce the well-formedness of biological entities through their rule-based formulation.

2.4 Related Works

A modeling approach presenting consistent visualizations of different concerns has been developed to ensure the cohesion between sub-views of an overall system metamodel [6]. However, it requires building a metamodel of the entire system at design time, which is unfeasible for biological entities.

Crop modeling efforts for smart agriculture have gone towards improving predictive yield models through dynamical representations of phenology [2] or through the integration of energy balance models to optimize yield in regards to power efficiency [19]. Such methods are limited by their lack of domain-specific system representations that would allow the grower to optimize his operations. On the other hand, models of crop morphology have been developed for the visualization of many crop types, such as tomato [14]. However, their application is limited mainly to characterizing genetic differences between crop cultivars via each model parameter.

Our approach distinguishes itself by co-simulating the crop and its growing environment to represent consistent views of phenology and morphology. By employing multi-paradigm modeling, our simulator is able to display multiple system concerns to its users while enforcing valid behavior through the well-formedness of the different modeling formalisms.

3 APPROACH AND UNIQUENESS

3.1 Overview

Our contribution aims to address two critical challenges in designing and developing digital twins for controlled environment agriculture: multi-paradigm modeling of the system and consistent representations of different crop concerns. By co-simulating the environment, crop, and the exchange of energy between the two entities, we can capture the ill-defined interactions between the crop and the growing environment. Then, we apply our model transformation to derive a possible morphological state of the plant via its simulated phenological state.

3.2 Co-Simulation

Our controlled environment agriculture system comprises many sub-systems. Some of those systems, such as the HVAC, irrigation, and lightning systems, are cyber-physical systems that operate through known laws of physics. Due to their cybernetical nature, they are typically event-driven systems that can be modeled with the DEVS [24] formalism. However, other parts of the CEA system are biological, and we do not fully understand their phenological or morphological dynamics. Rather, we approximate crops through known phenomena as systems of differential equations. Thus, the simulator that powers the digital twin must employ a multi-paradigm modeling approach able to couple discrete event systems with continuous dynamical systems. To address this, we built a co-simulation model to separate paradigms and integrate the different formalisms that compose a vertical farm, as shown on Fig. 1. The simulation details of each model and their coefficients are out of scope of this article, and will be available in an upcoming publication.

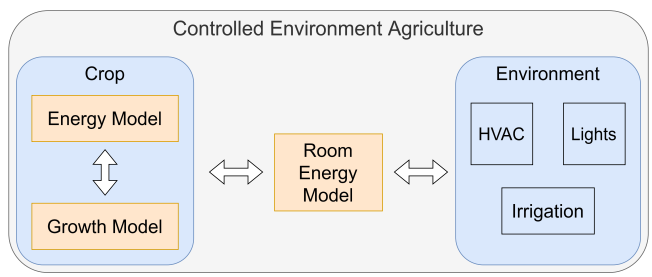

Figure 1: Co-simulation architecture of the vertical farm. Square boxes are individual models, orange boxes are continuous time models and blue boxes are discrete-event.

3.2.1 Environment. We first developed a discrete-event system specification (DEVS) [5] model of the growing environment that captures the power consumption of the many components that it comprises, such as the HVAC system, the irrigation system, and the lightning system. Each component sensor is modeled as an atomic DEVS (e.g. fans speed), then coupled to form coupled DEVS model of the cyber-physical system (e.g. HVAC). The DEVS formalism was implemented using the Python PDevs [23] library. This Python implementation leverages object-oriented programming concepts such as polymorphism to define a type structure for every sensor, enabling object-relational mappings to be integrated with most databases.

3.2.2 Crop. The mechanisms of crop phenology and its interaction with the atmosphere are crucial phenomena that characterize crop development. Typically, phenological models are implemented as differential equations that abstract certain cellular interactions, whereas gas exchange models typically involve thermodynamical systems. As such, it is difficult to derive a single system of equations representing the crop as it would require modeling its interactions with the environment, which are undefined. Rather, we co-simulate both phenomena using different formalisms and models. We simulated the phenology of a strawberry by implementing and adapting a tomato model [20] with a causal-block diagram in MATLAB Simulink and used an energy-balance model [10] implemented in MATLAB to compute the energy released by the crop into the atmosphere. MATLAB allows us to export our models as functional mock-up units (FMU), which contain compiled C code with an interface to execute the model, providing a fast implementation.

3.2.3 Room Energy. As the interactions between the crop and its environment are causal, we have to consider the atmospheric changes incurred by the crops for the next simulation time step. To do this, we solve an energy balance model based on the sensible and latent heat load exchanges between the HVAC and each crop. This way, we can infer the amount of water evaporated by each crop and soil based on sensor data, or predict the potential energy consumption of the HVAC.

3.3 User Feedback

3.3.1 Motivation. User feedback is an important part of the digital twin, as relevant information must be conveyed to the user to provide a reliable decision-support tool. Often, the behavior of the system is conveyed via a dashboard interface containing the relevant information, and depending on the use case, actuators control the system. However, such dashboards typically display direct sensor data, which may or may not be interpretable by an operator. For instance, a grower understands the crop's morphology and knows what organogenesis pattern may lead to better yield but cannot relate that knowledge to time-series sensor data capturing crop phenology. Thus, the digital twin for controlled environment agriculture must present the different concerns of the system to its operators using domain-specific representation based on models of phenology and morphology.

Phenological and morphological models capture domain-specific representations at different levels of abstraction. However, these models typically do not work jointly to provide a consistent view of the different crop concerns. As such, the models may conflict in their results by projecting different organogenesis patterns or providing mismatching estimates of the same KPI, such as leaf area index. By coupling the morphological model to its phenological counterpart through an abstraction of crop morphology, we can present consistent results at multiple levels of abstraction to the grower and agronomist while producing phenological and morphological indicators that guide CEA operations.

3.3.2 Transformation. We designed a model-based transformation to refine the phenological state of the crop produced by a simulator to a corresponding morphological state. We refine the phenological state to its morphological counterpart by optimizing the L-System model parameters using a genetic algorithm. This refinement is done through a domain-specific language that abstracts the crop morphology and specifies the desired morphological characteristics. For instance, we define the strawberry morphology by specifying the count of fruits and leaves. This DSL provides a simple way for the users to specify a desired morphological view and enables us to couple models of phenology and morphology by leveraging the well-formedness of the L-System model to obtain consistent representations of the crop concerns. As it is easily extendable within Java environments, we implemented our DSL with Eclipse XText and used XTend templates to configure the L-System model. To explore the space of parameters, we use the NSGA-III algorithm [7] implementation from the MOEA framework [11].

4 RESULTS

To evaluate our approach, we first calibrate the controlled environment agriculture simulator to reflect the behavior of our industrial partner's vertical farm and evaluate its applicability to simulate complex KPI. We then present the results of our model-transformation, where we transformed the phenological state of a simulated strawberry into its morphological state, and evaluate the accuracy of the produced crop morphologies.

4.1 Co-Simulation

The models that compose the production environment and its cyber-physical systems are based on energy balance equations or specifications from the equipment manufacturer, so they do not require calibration. However, both models that compose the crop rely on parameters that vary with crop species and cultivars. We thus provide an overview of our calibration process for the crop energy and growth models and refer the reader to the full thesis [4] for details.

4.1.1 Crop Energy Model. The crop energy model relies on coefficients for the internal and external stomatal resistances of the crop. Those parameters depend on genetic factors that are proper for each species and cultivar and need to be estimated empirically. This estimation process relies on complex, time-consuming, and destructive crop data that would be inapplicable to the next production cycle as crop seedlings change according to business needs. Thus, we used the coefficient from a generic evapotranspiration model [27] calibrated on tomatoes. This reliance on complex coefficients is a limitation of our model, but the model still exhibits adequate dynamics, as tomato and strawberry crops have similar photosynthetic pathways.

4.1.2 Crop Growth Model. The crop growth model relies on over thirty parameters, many necessitating expensive and time-consuming experiments with specialized equipment. As this experimental setup was unavailable, we kept most values from the initial model paper [25] originally calibrated on tomatoes. However, we had to assume the coefficient values affecting the reaction of the crop to temperature and organ growth rates. Using data collected during the production season of 2023, we calibrated specific coefficients for the sequencing of organ apparition.

4.1.3 Validation. We validate our approach using longitudinal data collected at Ferme d'Hiver over 57 days from the start of their March production cycle of the year 2023. The data included timestamped temperature, relative humidity, LED intensity, and PAR values at a biminute resolution. Data on crop phenology was manually collected at weekly intervals throughout the production cycle and involved tracking four specimens in four wall sections.

Our results show that we successfully co-simulated the interactions between the crop and the environment in a vertical farm. Through multi-paradigm modeling, we were able to capture the impact of crop development on the energy consumption of the system. However, the lack of experimental data limits the precision of our models, and we plan to collect further data to enhance their calibration. Further, the simulator takes over 10 minutes to produce a trace of the system on common hardware, which limits the exploration of the design space given the real-time considerations of digital twins.

4.2 User Feedback

Strawberry crops typically grown in colder outdoor climates benefit from controlled environment agriculture to control florescence patterns that optimize fruit yield [17]. Such patterns, known as thyrse, are not found in other crops [15] and require precise control of the environment through simulation to optimize development [8].

As this work is part of an ongoing project with an industrial partner, we refrain from showing results bound to intellectual property, such as our calibrated co-simulator output. To validate our approach, we generated representations for the Radiance and Brilliance cultivars from the Cropgro-strawberry [12] simulation model provided by the Decision Support System for Agrotechnology Transfer [13]. The model outputs a time series with counts of fruits and leaves but provides no information on branching patterns. We then use a heuristic function to translate the last phenological state into an abstract morphological state, assuming that a percentage of leaves are tri-lobed and others single-lobed. We then optimize over the count of fruits and leaves to obtain an optimal solution. An L-System VLab model developed by Lembinen et al. [15] generates a biologically accurate concrete morphological representation of thyrse architecture. Our early results show promise, as we can generate representations close to their target objectives. However, our model transformation is limited by the need for more data since we must find coefficients that map the phenological state to a morphological state and derive satisfactory parameters for our genetic algorithm.

5 CONTRIBUTION

Our contribution provides a simulation architecture and methodology for practitioners of controlled environment agriculture to build digital twins. To summarize the main contributions of our work, we: (i) developed a co-simulation architecture able to capture interactions between the crop and its environment; (ii) implemented an optimization-based instance-to-instance transformation to refine the output of a crop simulator into a consistent visual representation of the crop morphology and; (iii) provided an MDE-based methodology to visualize multiple crop concerns within a controlled environment agriculture system using domain-specific representations.

We have presented preliminary results on the applicability of our simulation architecture and model transformation. A full analysis of our experiments will be available in an upcoming publication and will delve deeper into the calibration of our genetic algorithm. We will expand on this work by collecting more data and calibrate our models further, and by integrating our co-simulation with our partner's infrastructure.

REFERENCES

[1] 2023. https://winterfarm.com/. [Online; accessed 31-July-2024].
[2] Amitrano et al. 2020. Crop management in controlled environment agriculture (CEA) systems using predictive mathematical models. *Sensors* 20, 11 (2020), 3110.
[3] Abbasi et al. 2022. The digitization of agricultural industry–a systematic literature review on agriculture 4.0. *Smart Agricultural Technology* 2 (2022), 100042.
[4] Archambault et al. 2023. Co-Simulation For Controlled Environment Agriculture. In *2023 Annual Modeling and Simulation Conference (ANNSIM)*. SCS.
[5] Concepcion et al. 1988. DEVS formalism: A framework for hierarchical model development. *IEEE Transactions on Software Engineering* 14, 2 (1988), 228–241.
[6] Cicchetti et al. 2012. A hybrid approach for multi-view modeling. *Electronic Communications of the EASST* 50 (2012).
[7] Deb et al. 2013. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. *IEEE transactions on evolutionary computation* 18, 4 (2013), 577–601.
[8] David et al. 2023. Digital twins for cyber-biophysical systems: challenges and lessons learned. In *2023 ACM/IEEE 26th International Conference on Model Driven Engineering Languages and Systems (MODELS)*. IEEE, 1–12.
[9] Fruth et al. 2017. Digitization in maritime logistics—What is there and what is missing? *Cogent Business & Management* 4, 1 (2017), 1411066.
[10] Graamans et al. 2017. Plant factories; crop transpiration and energy balance. *Agricultural Systems* 153 (2017), 138–147.
[11] Hadka et al. 2012. MOEA framework: a free and open source java framework for multiobjective optimization. *MOEAFramework-2.1-ManualFixed. pdf* (2012).
[12] Hopf et al. 2022. Development and improvement of the CROPGRO-Strawberry model. *Scientia Horticulturae* 291 (2022), 110538.
[13] Jones et al. 2003. The DSSAT cropping system model. *European journal of agronomy* 18, 3-4 (2003), 235–265.
[14] Lu et al. 2015. An improved visualization modelling method of greenhouse tomato plants based on L-system. In *2015 Chinese Automation Congress (CAC)*. 480–485. https://doi.org/10.1109/CAC.2015.7382548
[15] Lembinen et al. 2023. Diversity of woodland strawberry inflorescences arises from heterochrony regulated by TERMINAL FLOWER 1 and FLOWERING LOCUS T. *The Plant Cell* 35, 6 (2023), 2079–2094.
[16] Pylianidis et al. 2021. Introducing digital twins to agriculture. *Computers and Electronics in Agriculture* 184 (2021), 105942.
[17] Sønsteby et al. 2013. Environmental manipulation for establishing high yield potential of strawberry forcing plants. *Scientia Horticulturae* 157 (2013), 65–73.
[18] Schumacher et al. 2016. Automation, digitization and digitalization and their implications for manufacturing processes. In *Innovation and Sustainability Conference Bukarest*. Elsevier Amsterdam, The Netherlands, 1–5.
[19] Talbot et al. 2024. Development of a crop growth model for the energy analysis of controlled agriculture environment spaces. *Biosystems Engineering* 238 (2024), 38–50.
[20] Vanthoor et al. 2011. A methodology for model-based greenhouse design: Part 2, description and validation of a tomato yield model. *Biosystems engineering* 110, 4 (2011), 378–395.
[21] Valdés et al. 2018. Aviation 4.0: more safety through automation and digitization. In *Aircraft technology*. IntechOpen.
[22] Verdouw et al. 2021. Digital twins in smart farming. *Agricultural Systems* 189 (2021), 103046.
[23] Van Tendeloo et al. 2015. PythonPDEVS: a distributed parallel DEVS simulator.. In *SpringSim (TMS-DEVS)*. 91–98.
[24] Van Tendeloo et al. 2018. Discrete event system specification modeling and simulation. In *2018 Winter Simulation Conference (WSC)*. IEEE, 162–176.
[25] Egbert Heuvelink. 1996. *Tomato growth and yield: quantitative analysis and synthesis*. Wageningen University and Research.
[26] Aristid Lindenmayer. 1968. Mathematical models for cellular interactions in development I. Filaments with one-sided inputs. *Journal of theoretical biology* 18, 3 (1968), 280–299.
[27] Cecilia Stanghellini. 1987. *Transpiration of greenhouse crops: an aid to climate management*. Wageningen University and Research.