Community-Driven Adoption of Industry 4.0 Technologies for Sustainable and Resilient Food Production

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Abstract. Industry 4.0 technologies such as artificial intelligence (AI) and digital twins offer significant opportunities for improving sustainability and efficiency in food production. However, their adoption remains limited, especially among small and medium-sized enterprises (SMEs) and in contexts where manual operations are still necessary. This research presents a community-driven framework to support the integration of these technologies in local food production and agricultural systems. By combining technical development with community engagement, the research addresses both operational optimization and existing digital skill gaps. This research contributes to the broader digital and green transition by aligning advanced technologies with local needs, ensuring that innovation is inclusive, practical, and socially grounded.

Keywords: Industry 4.0, Digital twin, Community-Driven, Agricultural system, Sustainability

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1. INTRODUCTION

1.1 Objectives

The agricultural sector faces the dual challenge of increasing production efficiency while adhering to environmental sustainability and social inclusion goals. Industry 4.0 promotes digitalization with key enabling technologies including Artificial Intelligence (AI), Digital Twin (DT), Internet of Things, and cloud computing [1]. Proper application of Industry 4.0 technologies has proved to be effective in improving performance in various contexts including manufacturing. It is crucial to bring up the human elements; in developing technological solutions to ensure new developed technological solutions will not have a negative impact on society and particularly the local communities also support them. Yet, there is not much research done in integrating human needs and traditional knowledge when developing new technologies for food production and agricultural systems [2,3]. The green paradox concept refers to this phenomenon when the technological solutions developed to promote sustainable development leads to a negative impact because of not having a holistic approach and not including human behavior and social aspects in applying those technologies [4]. Despite the transformative potential of Industry 4.0, the agricultural sector has been slow in adoption of Industry 4.0 technologies.

In response to these challenges and needs, this paper aims to address this gap by proposing an innovative framework that allows responsible digital transformation that leverages the capabilities of Industry 4.0 tools in a community and socially responsible manner. The aim is to co- develop solutions that are technically advanced, socially inclusive, and environmentally sustainable.

1.2 Background

Industry 4.0 encompasses a suite of technologies that enable cyber- physical integration, data-driven analysis, and real-time decision support [5]. Key technologies include:

- Digital twins (DT): Virtual replicas of physical systems that simulate, predict, and optimize performance.
- Artificial intelligence (AI): Algorithms that enable machines to learn from data and support intelligent decision-making.
- Reinforcement learning (RL): A subset of machine learning where agents learn optimal actions by interacting with the environment and receiving feedback.
- Cyber-Physical Systems (CPS): Integrated systems in which physical processes are monitored and controlled by computer- based algorithms tightly coupled via networks.
- Cloud Computing: On-demand access to computing resources that enables scalable processing, data storage, and remote collaboration essential for real-time analytics and distributed digital twin deployment.
- Internet of Things (IoT): A network of physical devices embedded with sensors and connectivity that enables real-time data collection and interaction across systems. has applied these technologies to manufacturing and logistics, applications in agriculture remain fragmented. Moreover, a few approaches systematically incorporate community knowledge and behavioural dynamics into AI training and system design.

While existing works have applied these technologies on manufacturing and logistics sectors, their applications in agriculture remain fragmented. Limited research has been done for systematically incorporating community knowledge and social aspects into AI training and system design.

2. CONCEPTUAL FRAMEWORK

The proposed framework is structured around three pillars: socio- technical systems modeling, AI-based optimization, and community knowledge integration.

2.1 System-of-Systems Architecture

Agricultural systems are complex systems, due to including many sub elements that dynamically interact with each other [6,7]. Systems Engineering (SE) discipline focuses on the whole system and the interactions between its elements. Hence, this research proposes using SE to analyze an agricultural system that might lead to an underperforming when applying Industry 4.0 technologies. In the proposing framework, the agricultural system is conceptualized as a System-of-Systems (SoS) comprising interdependent subsystems such as production modules, logistics, labour allocation, and energy management [8]. Each subsystem is modeled as a module with a hierarchical structure to break down and manage the complexity of such a large-scale system.

This paper suggests modelling the architecture of an agricultural system by defining two categories of processes: transformative and supportive. The first category refers to processes that their functions contribute to transformation of inputs to outputs, such as planting, fertilizing, or harvesting processes. The second one refers to processes that their functions support the first category or are implemented to improve an agricultural system performance such as data acquisition for maintenance planning. Processes from both categories can interact with each other. A process can have physical or operational enablers to deliver its functions. Interactions between processes are defined by indicating type of interactions among their functions, such as data or physical exchange. This allows defining interactions at functional space of an agriculture system, shown in Fig. 1.

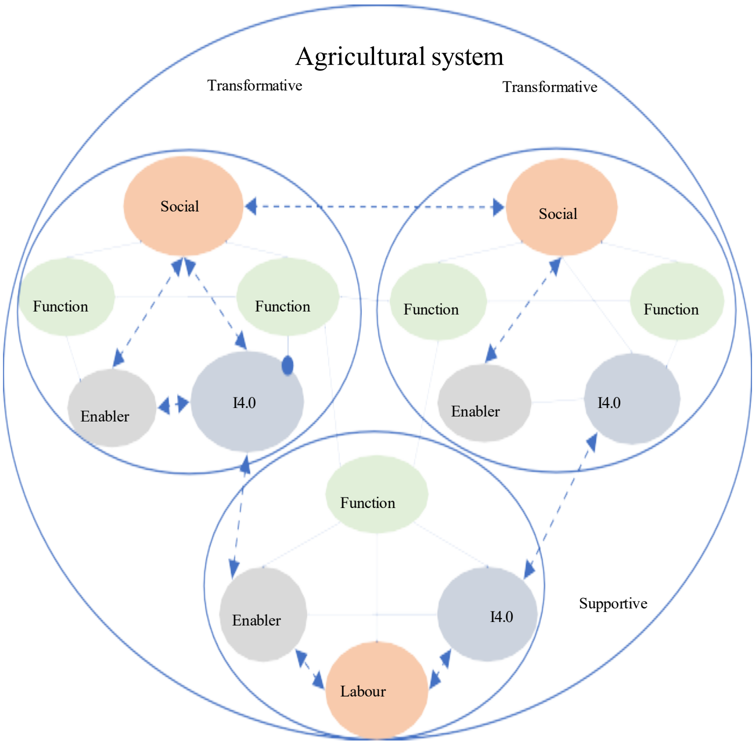

Fig. 1. SoS architecture of an agricultural system

2.2 Modelling the interactions in SoS Architecture

Application of Industry 4.0 may require adding supportive processes which expand the scale of an agriculture system. Implementing new technologies in transformative processes also increases the system complexity due to forming new interactions between enablers. Here, the consequences of integration of Industry 4.0 technologies in an agriculture system are discussed.

This paper suggests an innovative approach by developing DT of an agriculture system with a State-based Modelling formalism (SM). SM demonstrates a system with a set of states, transitional conditions between them, and consequent actions. This paper suggests modelling an agriculture system at the highest level of hierarchy as a parent state that includes transformative and supportive processes. The modelled states for processes (called process-states) can include substates to embody their needed enablers (called enabler-states) to deliver their functions. Transitions between process-states and enabler-states can be defined to embody the logic of interactions between processes and enablers.

The resultant DT model has a nested state structure, which the higher levels embody an agriculture system and its processes, while detailed modelling can be defined for enabler-states. A process-state can include several sub states to embody various types of enablers including Industry 4.0 and human. Each enabler-state can be further decomposed to model the disciplinary details, their behaviour, and their interactions with other enabler-states. The enabler-states can model a specific enabler from two perspectives: first, modelling the dynamic behaviour of each enabler in its discipline at the system level to model its interactions with other enablers such as the movement of a human when loading a part on a machine, and second, providing a module for encapsulating its own specific behaviour such as the kinematic of a machine or modelling the behaviour of a human.

Such structure allows holistic and multidisciplinary modelling of an agriculture system. The proposed DT can embody different types of processes based on the levels of Industry 4.0 application (transformative and supportive processes) and different types of enablers (human and technical). State models can be simulated, mostly based on discrete event simulation (DES) approach [7]. Agriculture systems in general operate based on discrete events, hence, DES approach matches perfectly to simulate the dynamic interactions between enablers in DT of an agriculture system. Interoperation between enablers and process states can be modelled by defining proper variables and parameters. Since the nested state's structure allows encapsulating the modelling details of operators and Industry 4.0 technologies while their interactions can be modelled at a higher system level, the proposed approach allows observing the impact of including potential Industry 4.0 technology on both operators and overall performance of an agriculture system.

2.3 Socio-Technical System of Systems Digital Twin

This research considers an agriculture system a socio-technical system, because human, social, and technical components interact dynamically within it and its performance is determined by technical elements, including industry 4.0 technologies, and their interaction quality with human systems. This study places these human-technology interactions at the center of its modeling efforts.

To ensure a human-centered approach, this research suggests innovative modelling parameters to be implemented in the proposed DT and introduces Interaction Type (IT) parameters that capture how social or human elements engage with technological components. Three dimensions of interaction are defined:

- Functional role: In functional dimension three types of interactions can exist between a social aspect and an Industry 4.0 technology to deliver a function: independent co-existence, (IE), independent cooperation (IC), and dependent collaboration (DC).
- Interaction modality: In interaction modality, two types of interactions can be defined: physical (P) and information (I).
- Temporal pattern: In temporal domain, two types of interactions can be defined as: sequential (S), concurrent (C), and feedback (F).

For example, independent co-operation with exchanging information in a sequential manner, or (IC, I, S). However, some might not sound feasible, such as (IE, P, F). This research suggests defining this Interaction Type parameter, IT_{pi}= (function, physics, timing) for all the process-states in the proposed DT, where ‘p’ refers to a specific process and ‘i’ refers to a specific Industry 4.0 technology. This enhances awareness about the existence of interactions that can lead to consequences. Otherwise, the interactions maybe overlooked, and their unintended consequences can negatively impact human or AS performance.

This research suggests modelling specific parameters indicating various social needs in the proposed Digital Twin. The social needs can include safety, health, belonging, esteem, and self-actualization. This research suggests defining a parameter called Interaction Consequence on social needs, to indicate the level of social needs satisfaction because of interactions as given in Equation (1).

$$ICH_{pi} = \{[IT_{pi}], \text{[level of needs' satisfaction)]} \qquad (1)$$

Various qualitative and quantitative approaches can be used to define the level of satisfaction, such as Likert Scale, surveys, and fuzzy logic.

2.4 Reinforcement Learning for Community Driven and Socially Responsible Development

The proposed digital twin framework integrates a reinforcement learning (RL) model as a central decision support system. RL is particularly effective for learning optimal strategies in environments characterized by uncertainty, complexity, and dynamic interactions — all of which are prevalent in agricultural production and supply chain systems.

In the proposed framework, RL agents interact with a high-fidelity simulation environment generated from the digital twin. This environment models real-world agricultural workflows using discrete- event and state-based simulation methods. Agents observe system states composed of variables such as energy consumption, crop yield, environmental conditions, equipment availability, labour status, and sustainability metrics.

Each agent operates within a Markov Decision Process (MDP), where the state space includes continuous and categorical features and the action space spans operational decisions such as irrigation levels, resource allocation, worker assignment, and scheduling. The agents are trained to maximize a composite reward function that can incorporate various related parameters such as:

- Crop yield efficiency
- Resource and energy optimization (evaluated using life cycle analysis metrics [8])
- Operational costs
- Social and ethical considerations derived from community preferences
- Penalty terms for rule violations (e.g., exceeding carbon thresholds or worker fatigue levels)

Deep Reinforcement Learning (DRL) techniques such as Proximal Policy Optimization (PPO) or Deep Deterministic Policy Gradient (DDPG) can be employed to manage the complexity of continuous, multi-objective decision spaces. These methods leverage neural networks to approximate policy and value functions and are trained through extensive interaction with simulation. Model performance is assessed based on learning stability, convergence speed, and long-term generalizability across diverse agricultural scenarios.

2.5 Community Knowledge Integration into RL Policy

To ensure responsible and inclusive digital transformation, traditional and local community knowledge is explicitly integrated into the RL framework. This process bridges qualitative social knowledge with quantitative learning systems, allowing the RL agent to develop policies that are both effective and socially legitimate. The integration process involves several stages:

1. **Knowledge Acquisition:** Community workshops and expert panels are conducted to elicit experiential knowledge. Data are structured into three key categories:
    - Behavioural rules: If-then patterns and cultural norms around farming operations
    - Environmental observations: Indicators of seasonal changes, weather, pest conditions
    - Adaptive strategies: Local responses to past disruptions or climatic extremes

2. **Policy Shaping:** Collected heuristics guide the initialization of the RL agent's policy network. This can be achieved through:
    - Initial biasing of the action selection probabilities
    - Constraints in the exploration space to prevent culturally unacceptable actions
    - Prioritized replay based on context relevance

3. **Reward Shaping:** Community priorities — such as soil preservation, water conservation, or labour fairness — are translated into additional reward terms or reshaped reward functions. These are assigned weights based on feedback from stakeholder consultation using methods like fuzzy logic or weighted Delphi consensus scoring.

4. **Simulation Constraints:** Practices deemed essential or non- negotiable (e.g., bans on certain chemical use, ceremonial land-use boundaries) are modelled as hard constraints in the environment. RL agents cannot violate these constraints during training or execution, ensuring cultural integrity is preserved.

This hybridized RL setup — combining technical optimization with socio-cultural alignment — allows the system to learn context-aware policies that generalize across different agricultural setups while respecting local wisdom. It also strengthens trust in AI-assisted decision- making by ensuring transparency and inclusion in the model development process. The proposed approach takes a step in covering the explained research gap while having a direct societal impact by empowering communities with new competencies and fosters a co-development approach where traditional knowledge contributes to the research process.

3. IMPLEMENTATION AND TOOLCHAIN

The proposed framework employs a modular digital twin model that can be built in various platforms such as

MATLAB Simulink and Sim Events for discrete events and state-based modeling. Key components include:

- Baseline simulation of agricultural workflows.
- Scenario testing (e.g., equipment failure, weather variation).
- RL agent training using model-integrated reward functions.
- Agent based modelling within state -based modelling architecture to simulate human behaviour, labour interactions, and decision-making routines.
- Interface modules to evaluate interventions such as automation, renewable energy integration, or logistics reconfiguration.

4. CONCLUSION AND FUTURE WORK

The presented framework bridges the gap between advanced Industry 4.0 technologies and socially responsible digital transformation in agriculture. By integrating reinforcement learning with community- derived knowledge into a modular digital twin system, the approach enables context-aware optimization while preventing unintended consequences of decontextualized technology deployment. This research fosters inclusive digital transformation by embedding local knowledge and values into advanced optimization tools. It addresses systemic challenges in technology adoption by:

- Empowering communities to influence AI behaviour.
- Providing decision support tools tailored to local contexts.
- Promoting sustainable, resilient agricultural practices aligned with net-zero goals.

Future work will explore the implementation of the proposed framework on a real case study to validate it. Also, cyber-physical integration with real-time sensor data, expanding applicability to other critical sectors such as logistics, water management, and renewable energy systems can be further explored.

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