IoT-Based Smart Monitoring and Automation for Yield Optimization in Roll-to-Roll Manufacturing

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Abstract

With Roll-to-Roll (R2R) manufacturing, the web-based material can be continuously processed through a series of manufacturing operations and allows important high-throughput manufacturing processes for flexible and printed devices. The continuous process production however is not without its challenges, as stable process conditions, and maintaining consistent product quality is difficult to achieve. Process parameter variations can result in defects, mis-registering issues, material loss and production yield loss. The field of R2R processing has already been shown to be applicable to flexible devices, and different studies have explored flexible sensing, scalable polymeric sensing, self-powered sensing, R2R compatible sensor fabrication, AI, and approaches of digital-twins.

This paper suggests a conceptual framework for smart monitoring and control system in yield optimization of R2R manufacturing based on the Internet of Things (IoT). The suggested architecture links the physical manufacturing process to a distributed network of sensors, data acquisition, access to edge and cloud, real-time monitoring, data analytics, predictive modelling using AI capability, a digital-twin model and a decision support system. Measuring and processing of the process and the environment would occur on an ongoing basis to detect any abnormal conditions, assess potential quality issues and contribute to predictive decisions.

Digital-twin concepts could enable a virtual representation of the R2R process, making real-time sensor data and predictions possible.

Contribution is expected to be a system-level framework at the level of the R2R process, which connects physical process conditions with the digital process monitoring, predictive process analysis, and yield-guided decision-making. The study is not empirical and is not reported to have been tested, or measured to have a high prediction accuracy, nor shown to improve yields. Instead, it is a stepping stone towards a future prototype and experimental study. This proposed framework may offer a way to more connected, predictive, and responsive R2R manufacturing systems.

Keywords

Internet of Things (IoT), Roll-to-Roll Manufacturing, Smart Manufacturing, Yield Optimization, Real-Time Monitoring, Flexible Sensors, Artificial Intelligence, Digital Twin.

1. Introduction

1.1 Background of Roll-to-Roll Manufacturing

A continuous manufacturing process is the roll-to-roll (R2R) process, where flexible printing material (typically called a web) is carried from one roll through a series of manufacturing processes, and is then wound onto another roll. R2R systems are continuously conducted on a moving substrate whereas discrete manufacturing is conducted on individual items. This makes the technology interesting for high-throughput/high area manufacturing, such as flexible and printed electronics.

R2R processing is one of the key manufacturing methods for implementation of flexible devices and is related to future Internet of Things (IoT) era, as discussed by Morrison (2016). The processing ability of flexible materials continuously brings in important opportunities of the case of scaling production. Continuous production also produces a need for consistent conditions of the process as a variation in one step of the process can impact material which goes through another step of the process. The maintenance of process stability is thus closely related to the process quality and loss in production.

Several interconnected operations such as web handling, printing, coating, heating, drying and other material processing operations may be used at R2R manufacturing. Several process variables may influence the quality of the final product more than just a single variable. Thus, the following aspects are needed to obtain data for effective monitoring: 1) data for different phases of the production process and 2) an ability to connect different measurements in the process to outcomes of production.

1.2 Monitoring Challenges

Because of the continuous production process, there are specific monitoring needs in R2R manufacturing. During the production process, the print speed, tension, temperature, pressure, ambient humidity, material properties and printing conditions can change. Positioning and lining are also among the factors that must be accounted for in multi-layer/exposed printing methods since it is necessary to have suitable positional relationship between successive patterns.

To gather the importance of the relationship between the printing process parameters and the registration errors, and explore the digital-twin concepts for R2R gravure printing, the authors of this paper (Shakeel et al. 2023) investigated in this paper. Through their tasks, they demonstrate how useful it is to move beyond measuring to predicting outcomes related to the process. In the case of the proposed framework, this is a valuable consideration to include real time process information as an input into a predictive manufacturing system.

1.3 IoT-Enabled Manufacturing

IoT can help establish links between the physical manufacturing process and digital information system. In the proposed R2R architecture, the basic relationship can be represented as:

Physical process, sensing, communication, data, analytics and decision-making.

Smart sensors gather data from the manufacturing environment, data-acquisition devices process the data, and communication infrastructure conveys the information to edge or cloud platforms. This information can then be analysed using analytical systems to obtain information for monitoring and decision support.

Manoharan et al. (2026) offer a wider surveillance on manufacturing digitalization and the role of AI, which backs the shift towards a smart factory environment. The importance to R2R production is that while this continuous/original data generation work may provide precursors to building process patterns and production patterns of service behavior which are capable of predicting the process issues instead of full production based inspections.

Initiatives for flexible and scalable sensor technologies.Development efforts for scalability and flexibility of sensor technology.

The sensing layer is the basic component in the proposed proposed architecture of IoT. Printed flexible temperature and humidity sensors are considered in the light of the suggestions of

Rubio and Bolduc (2025). The flexible sensors are potentially interesting for distributed monitoring, they can be designed for multiple sensing locations and flexible substrates.

Kumar et al. (2026) also talk about polymeric sensors for scalability, sustainability, environment monitoring and low-temperature fabrication. All characteristics have a bearing on using distributed sensing in continuous manufacturing processes. The selection of the sensing technology should not only be influenced by the parameter to be measured but also by the scalability, manufacture compatibility, durability and integration parameter.

On the other hand, another dimension is added by the self-powered sensing using triboelectric nanogenerator (TGN) technology as introduced by Wu et al. (2025). The use of selfpowered approaches may offer potential solutions for sensing locations where traditional power provision may be impractical. Depending on the application one might think of (R2R), the technologies could then become part of future distributed monitoring architectures, but would need to be assessed experimentally to verify their suitability.

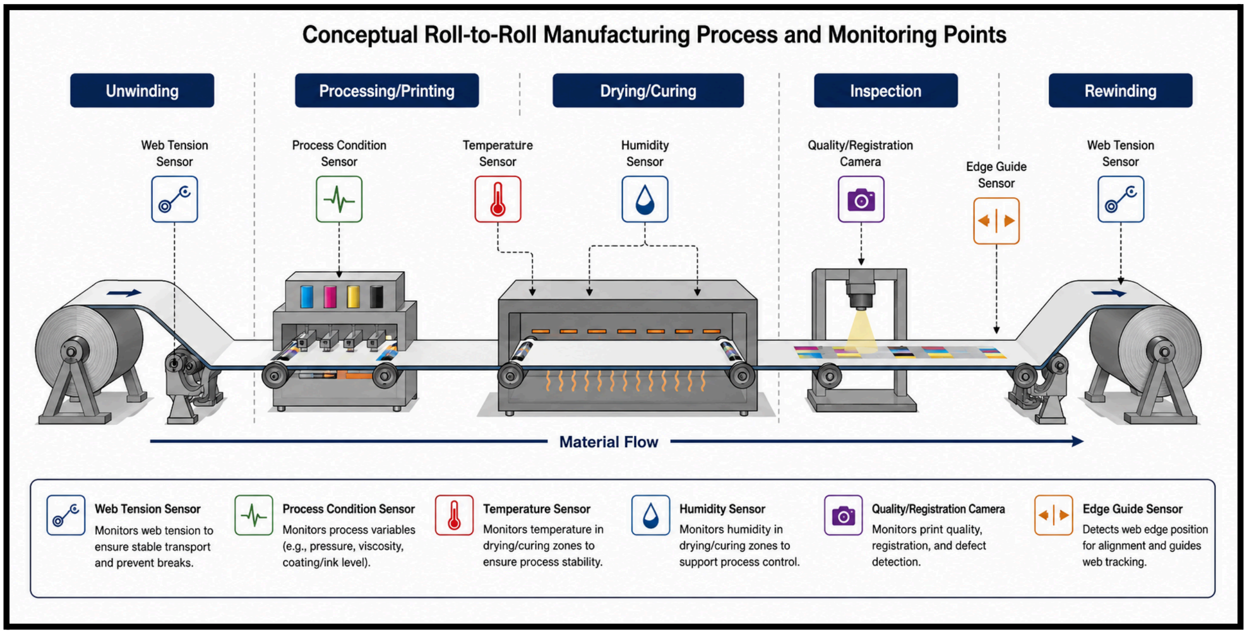
For R2R manufacturing, a sensing device made using SWCNTs in gravure is provided by Sun et al. (2026) with a direct connection between the R2R manufacturing steps and the sensing device. This shows the effectiveness of R2R-compatible fabrication for the scalable development of sensors and highlights the potential to connect sensing technologies to flexible manufacturing techniques.

1.5 is another research paper that was submitted by students for a different topic.

Even though the reviewed studies address important aspects of the smart manufacturing in R2R, they concentrate on various technological areas. They are pictured distinctly, one for each aspect of R2R manufacturing, flexible sensing, scalable polymeric sensing, self-powered sensing, R2R-printed sensing, AI-driven manufacturing, and digital-twin prediction. The next hurdle to come is integrating these into a single monitoring environment targeted towards real-time quality monitoring and yield optimization.

The aim of this study is then the development of a conceptual IoT-based smart monitoring system that can gather, transmit, analyse and interpret the R2R manufacturing process data for real-time quality monitoring and yield optimisation.

Figure 1 — *Conceptual Representation of Roll-to-Roll Manufacturing and Monitoring Points*



The figure illustrates the basic operating concept of a Roll-to-Roll (R2R) manufacturing process in which a continuous flexible substrate is transported from an unwinding roll through sequential manufacturing stages and finally collected on a rewinding roll. The process includes representative stages such as material unwinding, printing or processing, drying or curing, inspection, and rewinding. Monitoring points are distributed along the production line to represent the proposed collection of process and environmental information. The figure establishes the physical manufacturing environment in which IoT-based monitoring can be implemented.

2. Methodology

2.1 Research Design

In this research, the design-oriented and conceptual system-development is adopted. Has not developed or tested a physical monitoring system. Rather, the methodology aims to strive to build the functional structure of a proposed IoT architecture by leveraging the technological capabilities that have been identified in the literature.

The development process starts with defining requirements and process conditions for R2R manufacturing that can affect stability and quality. Relevant measurable properties are then taken into account and technologies of sensors suitable to the intended monitoring activities are selected. Afterwards, data-acquisition and communication are linked conceptually to the sensing system, followed by data-processing, AI-based data analysis, digital-twin integration, and yield-oriented decision making and information support.

The methodology is then applied in the following way:

Monitoring requirements and sensor selection, data acquisition, communication, data processing, AI prediction, creation of digital twin, decision support, and yield optimisation.

2.2 Proposed System Architecture

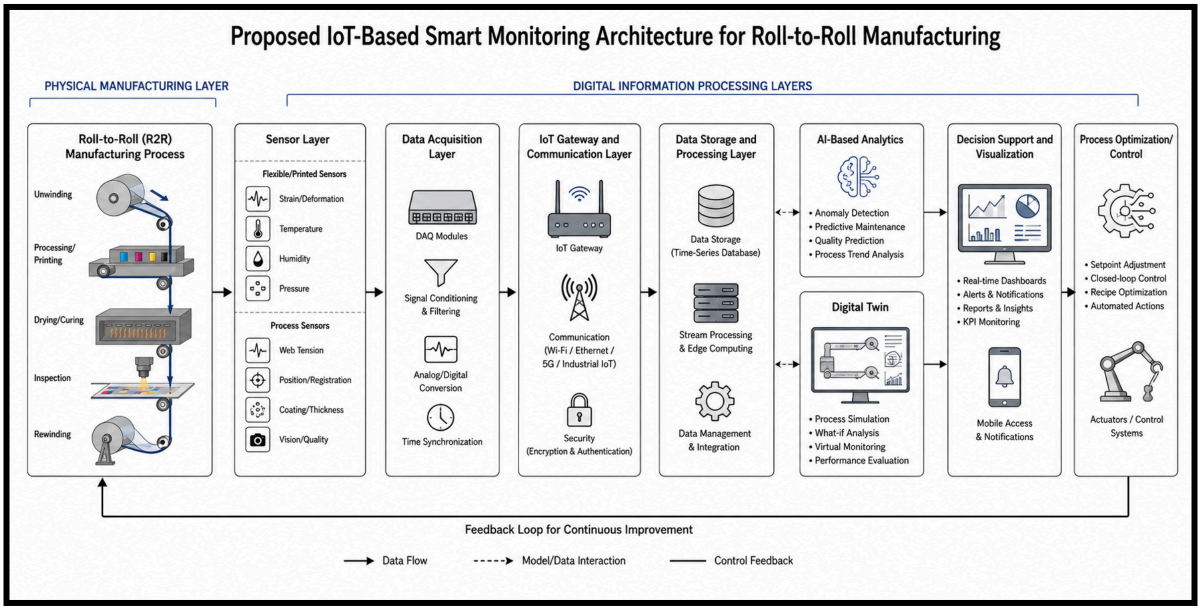
The proposed architecture is a layered solution that is interconnected. The physical manufacturing layer is the physical R2R manufacturing equipment, web materials, rollers, printing/coating, heating and drying processes, and the final product.

The sensing layer supplies measurements from the proper locations. Readings of temperature and humidity are especially helped by Rubio and Bolduc (2025). The monitoring during the registration is applicable to the work of Shakeel et al. (2023) and some other factors like tensions, speed, pressure and vibration are proposed engineering factors of the cited works but not experimentally proven.

Data-acquisition layer: This layer collects data from the sensor through a means of sensor node, micro controller or any other proper data acquisition device. They would be dated, and if needed, would be connected to sensor location and/or manufacturing phase. Noise management, erroneous data elimination, data normalization and synchronization would be part of the pre-processing.

At the communication layer they would interface between the sensors and the gateway that would connect to the edge or cloud platform. We did not specify a particular communication technology because the technology solution required will depend on the context in which the device will be used for manufacturing, sampling, network conditions and response requirements.

Figure 2 — *Proposed IoT-Based Smart Monitoring Architecture for R2R Manufacturing*



The figure presents the proposed architecture for an IoT-based smart monitoring system for R2R manufacturing. The architecture consists of interconnected layers beginning with the physical R2R manufacturing process and sensing layer. Sensor measurements are transferred through a data acquisition layer and IoT communication infrastructure to a centralized data processing environment. The processed information is subsequently analyzed using AI-based analytical methods and connected to a digital-twin representation of the manufacturing process. The resulting information is provided to a decision-support layer, which can assist with process optimization and provide feedback to the manufacturing process.

2.3 Data Analytics and AI

Processed sensor data would be loaded into a sensor analytics workflow which would include:

Raw data can be gathered for use in pre-processing, feature extraction, anomaly detection, prediction, and decision making.

For some applications an anomaly detection methodology would be able to identify differences in operating conditions from the norm, and for a predictive model, there would be an analysis of the relationships between the operating conditions and possible quality outcomes. One type of application would be “Registration-error prediction,” as discussed by Shakeel et al. (2023).

AI might also help identify conditions which can result in reduced yield. For this reason however, no particular AI model and performance level is stated as the results of the experiments were not obtained and model validation is not possible.

2.4 Digital-Twin Integration

The intent of the proposed DIGITAL TWIN is to create a virtual model of the physical R2R manufacturing process. The information generated through sensors would be feed into the digital representation, predictive models would take the process state into account to facilitate analysis and decision making.

This conceptual relationship is:

Physical R2R process ↔ Sensor data ↔ Digital model ↔ Prediction ↔ Decision.

This concept is used as a principle basis by Shakeel et al (2023) since it is related to digital-twin implementation in R2R gravure printing and prediction of registration-errors.

2.5 Yield Optimization

Conceptually the yield is defined as:

$$[Yield(\%)=\frac{N_{acceptable}}{N_{total}}\times100]$$

where, $N_{acceptable}$ is the acceptable output, and N_{total} is the total production output.

This proposed system would aim to be able to show conditions for possible quality degradation and acceptably lower output. The plan is to make the decision via:

Detection, Prediction and Decision, Process adjustment, Potential yield improvement.

The improvement of yield is not claimed in the framework. It would be necessary to provide the proof of measurable improvement that would take the form of the experimental implementation of the proposed monitoring and decision support approach.They only way to prove the effectiveness of the proposed monitoring and decision.support would be to be experimented and carried out in the real world.

2.6 Proposed Validation

Future experiments to be performed would start by sensor calibration and characterization, followed by controlled R2R experiments under different process condition scenarios. The readings from the sensors, along with needed product-quality data would be gathered with the data. The resulted data set could be used to train and validate predictive models.

Future studies may take into account accuracy of sensor, data reliability, anomaly detection accuracy, prediction accuracy, manufacturing yield variations, or the prediction of registration error (if applicable). Production could be compared with the proposed monitoring framework in order to determine the baseline production.

3. Literature Review

3.1 R2R Manufacturing.

Morrison (2016) points out that R2R processing is an important option for flexible devices and components, and associates these roadmap moves to the new IoT era. The constant flow of material on the web presents a process condition that allows for manufacture to be conducted at the high throughput levels. But, the continuous process can result in a significant amount of process variation in the product prior to discovery.

This makes a compelling basis for ongoing process monitoring. Contrary to the idea of quality having to be assessed solely post production, R2R systems can benefit from information that can be provided as production goes on. As such, the physics described during the discussion by Morrison introduces the world of manufacturing that provides the context for the proposed IoT architecture.

3.2 Digitalization and AI

Manoharan et al. (2026) illustrate the value of digitalization and AI-based models in manufacturing optimization in general. They are contributing to the shift in systems manufacturing towards one where digital technologies have a role to play, not just in data storage, but in analysis and intelligence decision making.

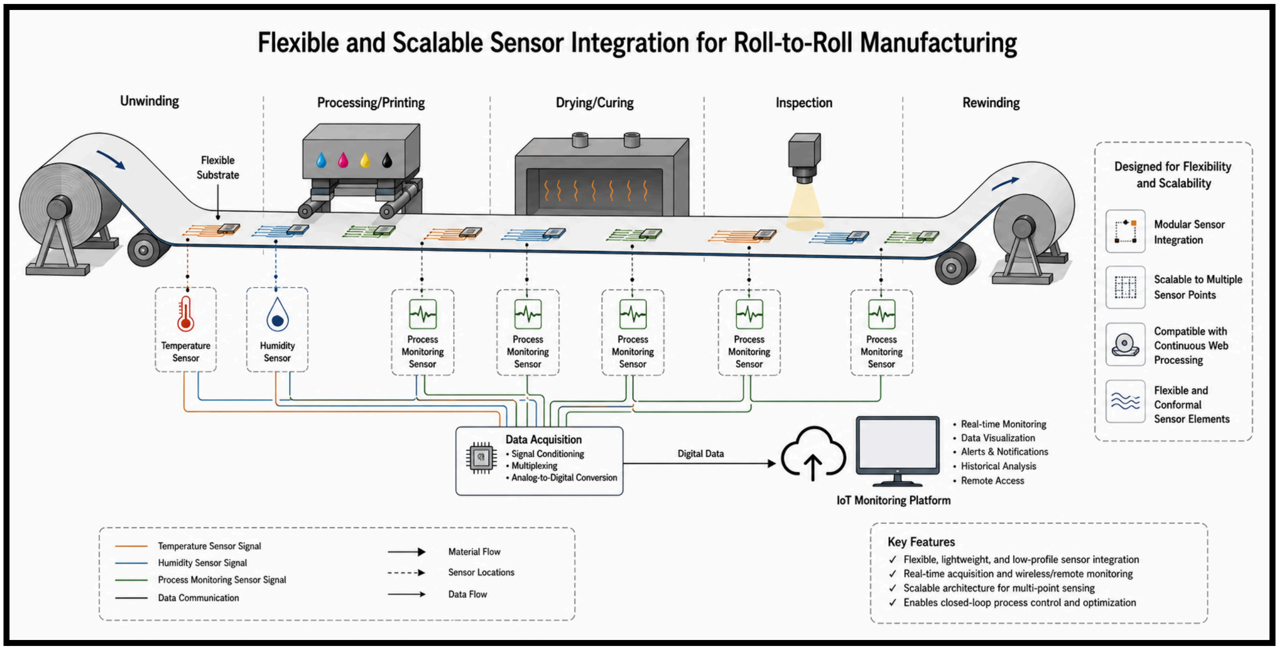
This is especially important for R2R manufacturing as large quantities of time-dependent data can be generated in a continuous process. AI has the potential to detect the relationships among several variables and help predict bad manufacturing processes. The value of analytical applications of AI, however, lies in the quality and representativeness of the data generated by the sensing system.

3.3 Flexible and Polymeric Sensors

Rubio and Bolduc (2025) laid the groundwork for the flexible temperature and humidity sensors. It involves their potential application in the proposed framework as a means of distributed sensing. Measuring temperatures and humidities can be used to convey information regarding environmental and/or process conditions with particular sensitivity if materials and/or functional layers are sensitive to environmental change.

From the sensing point of view, Kumar et. al. (2026) bring in polymeric sensors with traits pertaining to scalability, sustainability and low-temperature fabrication. These studies collectively indicate that sensor technologies with measurement capability are needed in future distributed monitoring systems that have aesthetic manufacturing and deployment properties.

Figure 3 — *Flexible and Scalable Sensor Integration for R2R Monitoring*



The figure illustrates the conceptual integration of flexible and scalable sensors with an R2R manufacturing line. Flexible sensor elements are positioned on or adjacent to the continuous substrate to enable distributed monitoring of relevant process and environmental conditions. Temperature and humidity sensors are represented as examples of flexible printed sensing technologies, while additional monitoring points represent other process variables that may be incorporated depending on the specific R2R manufacturing configuration. The sensor outputs are connected to a data acquisition system and subsequently transferred to the IoT monitoring platform.

3.4 Self-Powered and R2R-Compatible Sensors

Both self-powered sensing technology with triboelectric nanogenerators is introduced by Wu et al. (2025). This brings an energy contribution to distributed IoT sensing. If wired, battery-powered or traditional power sources are impractical, then self-powered sensing could be an alternative that should be explored.

Sun et al. (2026) offer an even tighter coupling between R2R manufacturing and sensing by introducing an SWCNT ring oscillator for flexible sensing which is gravure-printed. The importance of this work for the proposed framework is related to the fabrication of the sensors, which can be related to scalable processes compatible with the R2R approach.

These studies all come to the conclusion that the sensing layer of an intelligent R2R system may become flexible, distributed, scalable, and in some instances, even self powered. But those technologies have yet to be combined with data acquisition systems, communication networks, analytics, and decision making machines/objects in order to eventually play a role in an intelligent manufacturing system.

3.5 Digital Twins and Process Prediction

The relationship between digital twins and R2R manufacturing is the strongest direct connection made by Shakeel et al. (2023). They discuss R2R gravure printing and prediction of printing process parameters due to the limitations of registration errors. This proves the power of digital models for linking conditions of the process and its predicted manufacturing behaviour.

A benefit of the proposed architecture, with the digital twin, is a linkage between physical measurements and their analytical meaning. A digital model can show context for prediction and decision making, for example, given the status of the manufacturing process being sensed by its sensors. This is a complement to the usage of artificial intelligence as a tool for digitalization as explained by Manoharan et al. (2026).

3.6 Literature Synthesis

A set of complementary technological capabilities is identified in the literature. Morrison (2016) gives the R2R manufacturing context, while Rubio and Bolduc (2025) give flexible temperature and humidity sensing, Kumar et al. (2026) give scalable polymeric sensing, Wu et al. (2025) give self-powered sensing, Sun et al. (2026) give R2R-compatible sensor fabrication, Manoharan et al. (2026) give the AI and digitalization perspective, and Shakeel et al. (2023) give the concept of digital-twin and the prediction of registration errors.

Integrating systems is then the key opportunity seen through this combination. Each of the technologies can be linked via an IoT-based architecture for these sensing, data acquisition, communication, analytics, prediction, digital representation, and decision support. Conceptually, this incentives framework is unaltered by the proposed yield-optimization framework. The overall findings from the literature indicate that individual blocks of the

proposed system have strong support from literature while there is a need for a system level integration of the individual systems. The biggest contribution of the proposed research is not the invention of a new sensor, AI algorithm or a new digital-twin technology alone. Instead, it concerns the conceptualisation of a structure that integrates these technologies to meet specific needs in terms of real-time monitoring and decision support for yield in R2R manufacturing. The integrated view is the starting point for the system architecture and methodology that are described in the following sections.

Table 1. Synthesis of Literature Relevant to The Proposed IoT-Based R2R Monitoring Framework

Research area	**Relevant source**	**Contribution to proposed system**
R2R manufacturing	Morrison (2016)	Establishes the continuous manufacturing context and relevance of R2R processing to flexible devices and the IoT era
AI and digitalization	Manoharan et al. (2026)	Provides the basis for intelligent analytics, manufacturing digitalization, and optimization
Flexible sensing	Rubio & Bolduc (2025)	Supports the use of printed flexible sensors for temperature and humidity monitoring
Scalable polymeric sensing	Kumar et al. (2026)	Supports consideration of scalable, sustainable, low-temperature polymeric sensor technologies
Self-powered sensing	Wu et al. (2025)	Introduces the possibility of self-powered sensing where conventional power provision presents challenges
R2R-printed sensing	Sun et al. (2026)	Demonstrates the relevance of R2R gravure printing to scalable sensor fabrication
Digital twins and prediction	Shakeel et al. (2023)	Provides a basis for digital-twin implementation, process modelling, and registration-error prediction

4. Problem Statement

While it provides a continuous production capability and the possibility to scale the flexible and printed technologies up, it is very challenging to have consistent process conditions across continuous production. Some deviations in process and environment can cause quality deviation, registration error, material waste, and carry a risk of decreased production yield.

Since manufacturing is ongoing during the material is making its way through various states of transport, then deviations might be identified later causing defects throughout sections of the web.

Several technological capacities surrounding the challenge (development and implementation of the integrated and adaptive solution) have already proven useful through research. There is a continuous production environment (R2R) and flexible/polymeric sensors offer potential sensor options for distributed measurement. Some of the problems of sensor-power are solved with self-powered sensing, while the R2R-compatible fabrication proves the feasibility of producing the sensors through scalable fabrication methods. Analytical capabilities are the use of AI and manufacturing digitalization and mechanisms for establishing connection between physical (RC) conditions and digital representations/prediction is the digital-twin approach.

The analyzed references do not link these capabilities into a single integrated system for an IoT based real-time yield optimization for R2R manufacturing, however. However, it is not the absence of individual technologies—it's the absence of a conceptual architecture that links together sensing, data acquisition, communication, analytics, prediction, DT representation, and yield-oriented decision support.

In this work, an integrated architecture for the Internet of Things monitoring is presented, a process of which the continuous production of manufacturing and environment sensing information can be transferred, analyzed and interpreted. The information gathered can be used to support decisions on yield and the use of AI-based approaches and digital-twin concepts is incorporated to support the anomaly detection and prediction process.

Firstly the conceptual development of the Smart Monitoring architecture for R2R manufacturing by applying IoT technology is obtained as the result of the study. The results are not based on experimental results but only on a developed design of the system.

The proposed architecture starts with the actual manufacturing environment of R2R. Information is gathered from relevant process and environmental places by using a distributed-sensoring system. The measurements are collected with data acquisition devices, timestamped and then processed and transmitted via an appropriate communication infrastructure.

This creates the following data pathway:

The data acquired by R2R is transmitted to Sensors, which then passes on to a Data acquisition, the Gateway, Edge/Cloud, Analytics, AI prediction, Digital twin, and Decision support.

Monitoring framework focuses on temperature, relative humidity and registration because of their direct relationships with the cited literature. Other variables like web tension, speed, pressure, vibration, and process variables quality such as Zigzag are suggested engineering needs to be considered in future implementation.

The AI section offers suggested analytical steps to take which will help with the detection of abnormal conditions and anticipate future quality issues. The possible application based on Shakeel et al., 2023 is called Registration-error prediction. On a larger scale, AI might analyze the correlations between process parameters and yield-related results.

The digital twin represents at a process-level the digital model, which can be fed by sensor data and can communicate with predictive models. This establishes a connection between the real time specific measurement and the digital process analysis.

Optimization pathway obtained:

Detection – prediction – decision – process adjustment – potential yield improvement.

Key note here is the term ‘potential' as this study does not show an increase in yield using the framework. The result is the architecture and the analysis way of investigating that in an experimental way.

Table 2. Proposed Monitoring Parameters for the IoT-Based R2R Monitoring System

Parameter	**Proposed sensor type**	**Monitoring purpose**	**Potential yield relevance**	**Evidence status**
Temperature	Flexible/printed temperature sensor	Monitor process and environmental temperature	Identify thermal deviations that may contribute to process variation	Supported by Rubio & Bolduc (2025)
Humidity	Flexible/printed humidity sensor	Monitor environmental humidity	Identify environmental variations affecting process conditions	Supported by Rubio & Bolduc (2025)
Web tension	Tension sensor	Monitor web stability during continuous processing	Identify conditions associated with process instability	Proposed engineering requirement
Registration	Position/vision sensing	Monitor alignment between printed or processed layers	Detect potential registration-related defects	Supported by Shakeel et al. (2023)
Web speed	Rotational/web-speed sensing	Monitor operating speed of the moving web	Identify deviations from intended operating conditions	Proposed engineering requirement

Pressure	Pressure sensor	Monitor pressure at relevant processing stages	Identify process-condition variations	Proposed engineering requirement
Vibration	Vibration sensor	Monitor mechanical operating conditions	Identify abnormal equipment behavior	Proposed engineering requirement
Process-specific quality variable	Application-dependent sensor	Monitor product-specific quality characteristics	Directly relate process conditions to acceptable output	Proposed according to application

The distinction between evidence-supported parameters and proposed engineering requirements is important. The table does not imply that every listed parameter has been experimentally demonstrated within the proposed system. Instead, it provides a starting point for selecting sensors during future prototype development.

5. AI Prediction Framework

The proposed AI framework transforms processed sensor measurements into predictive manufacturing information. The analytical sequence begins with raw sensor data, followed by preprocessing and feature extraction. The resulting features can then be supplied to anomaly-detection and predictive models. Anomaly detection would be used to identify conditions that differ from expected process behavior, while predictive models could estimate the likelihood of future quality deviations.

One potential application is registration-error prediction. Based on the work of Shakeel et al. (2023), relationships between printing process parameters and registration errors can provide a basis for predictive analysis. Within the proposed system, this concept could be expanded by combining registration-related information with other available process and environmental measurements. The objective would be to provide earlier information about potentially unfavorable manufacturing conditions rather than relying exclusively on detection after a defect has occurred.

The AI framework can therefore be represented as:

Sensor data → Preprocessing → Feature extraction → Anomaly detection → Prediction → Decision support.

The specific AI algorithm, training dataset, prediction accuracy, and model performance are not reported because these would require experimental data and model validation that are outside the present conceptual study.

5.1 Digital-Twin Framework

The proposed digital-twin component provides a digital representation of the physical R2R manufacturing process. Real-time sensor measurements would be used to update the digital representation so that it reflects current or recent manufacturing conditions. This creates a connection between the physical production system and its computational counterpart.

The digital-twin framework is particularly relevant to the proposed architecture because Shakeel et al. (2023) demonstrate the application of digital-twin concepts to R2R gravure printing and registration-error prediction. Within the proposed system, the digital twin could receive information from sensors, incorporate relevant process parameters, and interact with predictive models. Its output could then be used to support interpretation of current manufacturing conditions and potential future process behavior.

Conceptually, the relationship can be expressed as:

Physical R2R process ↔ Sensor data ↔ Digital model ↔ Prediction ↔ Decision.

This arrangement would allow future implementations to investigate potential process conditions through the digital representation before applying corresponding adjustments to the physical manufacturing system.

5.2 Yield Optimization Framework

The final result of the proposed system architecture is a yield-oriented decision-support framework. The system is designed to establish a continuous relationship between process monitoring and potential production outcomes. When sensor data indicate an abnormal condition, the analytical layer can evaluate whether the deviation represents a potential quality risk. Predictive models can then estimate the likely consequence of the condition, while the decision-support layer can provide information for an appropriate process response.

The proposed optimization pathway is therefore:

Detection → Prediction → Decision → Process adjustment → Potential yield improvement.

Yield can be represented conceptually as:

Yield(%)=NacceptableNtotal×100Yield(\%)=\frac{N_{acceptable}}{N_{total}}\times100

where NacceptableN_{acceptable} represents acceptable production output and NtotalN_{total} represents total production output. The proposed framework does not claim that yield has already increased because no experimental comparison has been conducted. Instead, it establishes the mechanism through which future experiments could determine whether earlier detection, prediction, and process intervention produce measurable improvements in yield.

Overall, the developed framework provides a system-level connection between R2R manufacturing, flexible and scalable sensing, IoT connectivity, AI-based analytics, digital-twin representation, and yield-oriented decision support. Its principal result is therefore the **development of an integrated conceptual architecture** that can serve as a foundation for future physical implementation and experimental validation. The proposed system provides a clear pathway for moving from isolated process measurements toward connected, predictive, and potentially more responsive R2R manufacturing.

6. Limitations

A number of constraints should be kept in mind when interpreting the proposed scope. The study is based mainly on seven selected sources and, thus, not on the entire R2R, IoT, sensor, AI, and smart-manufacturing literature. A more comprehensive systematic literature review, covering other technologies and architectures would be needed to make a more extensive comparison.

Secondly, there is no experimental validation of the framework. The accuracy of the sensors, reliability of the communication links, prediction accuracy, and actual yield improvement were not validated based on a real prototype, controlled R2R experimental runs, or experimental data. Therefore, any proposed benefits in performance are yet to be assessed.

The challenge of sensor integration comes with practical difficulties, too. The mechanical stress, vibration, temperature changes, contamination, and degradation, which may occur in sensors surrounding moving webs and manufacturing equipment, could result in long-term degradation. So would need to be studied calibration and durability.

Another restriction is that of data quality. Accurate and frequent measurements, complete datasets, noise management and appropriate synchronization are the key aspects of AI-based prediction. The quality of the collected sensor data might decrease the confidence in the later analysis.

Before using AI models in production decisions, there's a need for representative datasets and suitable validation. In the same way, a digital twin relies on the accuracy of the process model it is derived from and the quality of the real-time data within it. Lastly, the proposed architecture can change if different R2R manufacturing configurations are tried due to the different material, equipment, process and quality requirements, and operating conditions.

7. Discussion

The main innovation for the proposed approach is the blend of the technologies, which are generally regarded as independent parts of manufacturing intelligence. Tipton is creating a physical production environment with flexible sensors, to measure the environment all over it;

connectivity is provided by IoT; the analytical and predictiveness aspect is ensured by AI, and finally, the digital aspect of production is done by digital twins. Being able to connect all these components together makes it possible to build a more comprehensive link between the physical manufacturing conditions and the possible quality and yield decisions.

The integration is especially significant as the manufacturing quality will not likely be dependent on a single variable. Process conditions such as temperature, humidity, web movement, registration and others all interact. An isolated sensor (or a combination of sensors) might show a change in a parameter, but an integrated analytical architecture might be able to test for an increase in quality risk associated with changes in a set of parameters.

This can help to facilitate a transition from reactive quality testing to proactive quality control. Reactive inspection is used to locate faults after they have been identified. Running monitoring allows deviations of the process to be discovered during the production process. If predictive analysis can identify that the existing conditions are linked to a higher likelihood of upcoming quality issues, the operators or an automated system might be able to act to change that before significant faulty work is generated.

To this change over, there are some flexible and low-cost polymeric sensing technologies that can be used. Rubio and Bolduc (2025) illustrate the importance of printed flexible sensors for temperature and humidity, and Kumar et al. (2026) emphasize highlighting scalability, sustainability, and low-temperature fabrication in polymeric sensors. These properties could be significant where sensors need to be spread throughout a continuous production system.

Continuing the theme, an important manufacturing component is added by Sun et al. (2026) who report on sensor manufacture which is compatible with R2R. This indicates that manufacturing methods which are compatible with flexible and continuous production can be developed for the production of sensing technology. Therefore, the significance is not only the ability of a sensor to measure a parameter, but also the ability to manufacture technologies for the sensing process that are scaleable up to distributed monitoring.

Another possible route is via self-powered sensing. The authors correct exhibit that the TENG-based sensing is relevant in cases where traditional power sources are not easy to obtain. In an R2R IoT architecture, these technologies may be able to address some of the practical obstacles in deploying a distributed, sensing node deployment. However, they are not suited for R2R manufacturing per se and needs to be tested through experimentation.

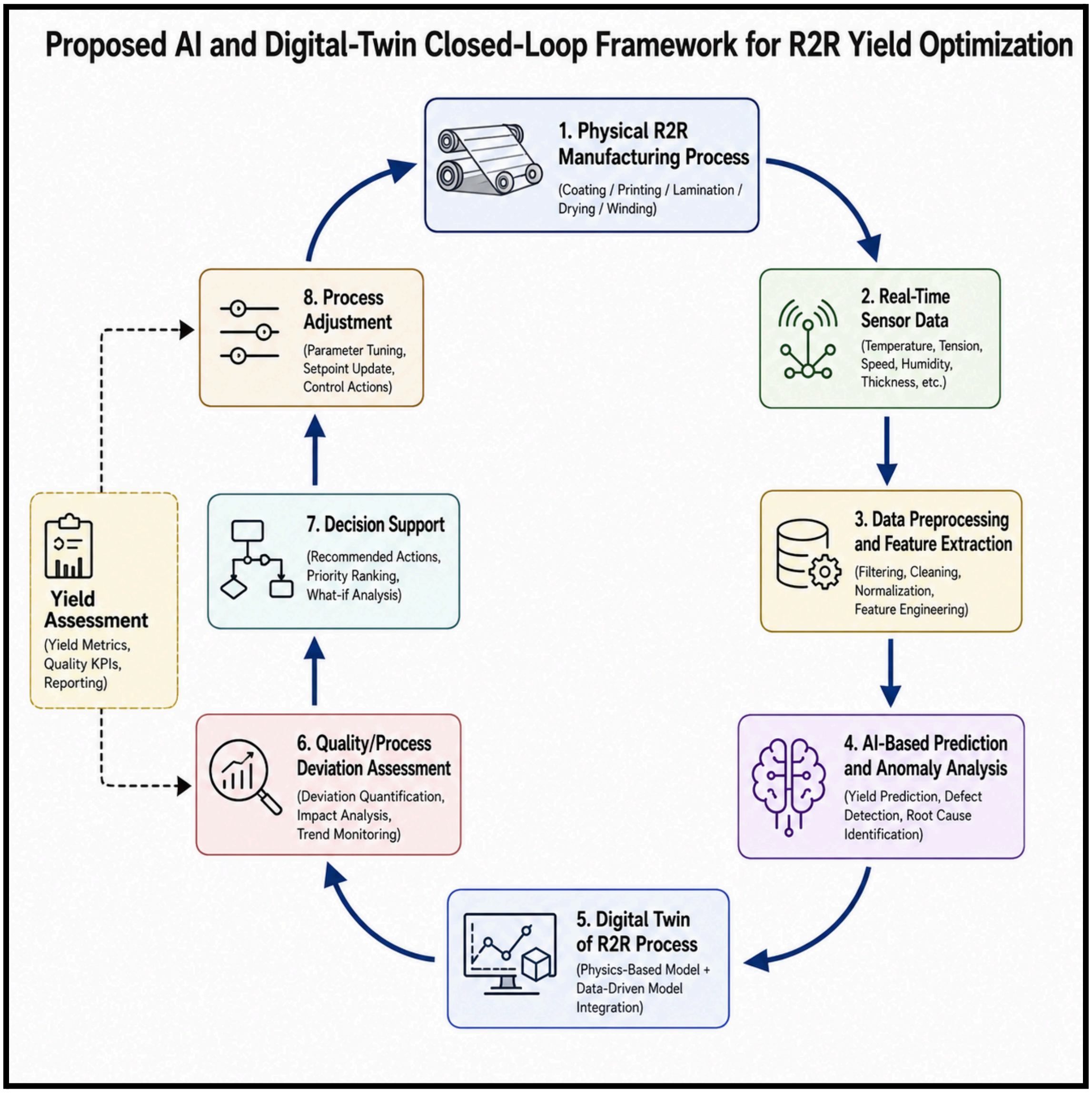
A key aspect of the capability that AI offers is the analytical element to enable the clustering of sensor measurements to produce potentially useful predictions. The ideas of Manoharan et al (2026) about digitalization are a part of the general trend of AI optimized manufacturing. The envisioned design would involve AI systems analyzing process data, looking for patterns, catching abnormalities, and forecasting potential quality issues. But, AI won't automatically give you good manufacturing decisions. It relies on high quality data, accurate modelling, validation and training data that can reflect real operating conditions.

Digital twins offer a different level – process level. Shakeel et al. (2023) put forward the topicality of digital-twin ideas for R2R gravure printing and registration-error prediction. The digital twin in the proposed framework can integrate the information retrieved from sensors and establish a representation of the physical process and serve as the context in which a predictive analysis can be performed. This can be a step toward instead of just recognizing a deviation, it might be investigating what the current state of the process have to say about the future.

These technologies work in conjunction generate therefore a conceptual connection between R2R manufacturing and flexible sensing, IoT, applying AI concepts, digital twins and optimizing yield. This doesn't mean that this integration has been proven to result in any performance increases as of yet. Instead, its value is the identification and structuring of the technological relationships necessary to look into the possible improvements.

The proposed structure is also the foundation for future automation. In case of the detection of a process deviation, AI might be able to estimate the extent of the deviation and the digital twin might offer process context and decision-support mechanisms could suggest a corrective action. In the future, this information may be used to tie in with process-control mechanisms. Properly introducing such automation would be of great importance, since any incorrective action may impact the product quality.

Figure 4 — *Proposed AI and Digital-Twin Closed-Loop Framework for R2R Yield Optimization*



The figure presents a closed-loop framework connecting the physical R2R manufacturing process with real-time sensing, data processing, AI-based analysis, digital-twin representation, quality or process-deviation assessment, decision support, and process adjustment. Sensor data generated during manufacturing are processed and analyzed to identify potential deviations and provide predictive information. This information is incorporated into the digital representation of the manufacturing process and used to support decisions concerning potential process adjustments. A feedback pathway returns the decision information to the physical manufacturing process, creating a continuous monitoring and *optimization loop. Yield assessment is incorporated into the framework to provide a basis for evaluating production performance.*

8. Conclusion

Though the R2R manufacturing offers an important avenue for continuous and scalable production of flexible and printed technologies, it is still a challenge to guarantee consistency of manufacturing process and product quality. Web movement through the process can potentially cause process deviations in future process steps that may lead to defects, material waste, and lower yield.

In this work, we designed a conceptual approach of smart monitoring and automation from IoT to resolving this problem. The architecture links the physical R2R process to distributed sensing, data acquisition, communication, data analytics, prediction via AI, digital-twin representation and decision support. Flexible and scalable sensing technologies offer potential means of acquiring process and environmental information, and IoT connectivity offers a route for passing the information from the sensor to the analytical system.

If the focus of inspection were to shift from reactive to proactive quality management, then real-time sensing might help with that. AI has the ability to analyze gathered data and detect unusual conditions or even forecast problems with quality, and digital-twin technology can serve as a virtual representation where real time measurements and forecasts can be linked into it. These components combine to form an "idea track" that leads from detection and prediction to decision and process adjustment and the possibility for yield improvement.

The study does not state that yield, prediction accuracy, sensor performance or process efficiency were improved, however. The proposed contribution is a conceptual system architecture that join together, the technological capabilities identified in the literature review to develop a consolidated R2R monitoring structure.

Therefore, future development needs should be directed towards implementation of physical prototypes, calibration of the sensors, controlled R2R experiments, collecting data, training and validation of the AI model, developing digital-twin and the quantitative evaluation of yield and quality performance. This will be followed by the physical implementation of the proposed framework and experimental validation in actual R2R manufacturing setting.

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