Digital Twins for Optimisation of Industry 5.0 Smart Manufacturing Facilities

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Abstract

Wide adoption of human-centered digital platforms may lead to novel collaborative business models promoting sustainable development. The paper proposes a procedure for optimizing the production process using the digital twin technology and considers a food packaging line as an example. To assure that implementation of digital twins contribute to growth of sustainable businesses by optimizing use of raw materials and energy, the modeling of production cycle is to be done with focus on the essential production data and human-friendly information representation.

Keywords

Digital Twin, Industry 5.0, Smart Manufacturing, Process Optimisation

1. Introduction

Environmental hazards and pressing societal risks make it vital to apply every effort pursuing the global development goals to ensure sustainability of production. Current stage of industrial development is known as Industry 4.0, with characteristic features being digitization of every sphere, automation of the manufacturing, omnipresence of the Internet of Things (IoT) devices. This allows efficient management of the mass production in changing external conditions, reducing production costs and increasing profits. However, Industry 4.0 fails to address the societal aspects of production therefore, conceptually new approaches for production systems design and management were proposed, known as Industry 5.0. Extensive literature is devoted to the refinement of the principles and features of Industry 5.0 and its relation to the Society 5.0 concept (see [1, 2] for reviews). For purposes of this study human-centricity of tech innovations (well-being of workers, human creativity role, collaborative robots) as well as mass customization and sustainability of manufacturing cycles are to be noted as key distinctions of the Industry 5.0 model.

Among many complex and distributed industries, food packaging stands out due to its wide presence, variety of product types and raw material types used. Predominantly, small or medium enterprises (SMEs), involved in food packaging, can benefit greatly from transformation of their businesses and such a transformation can be also beneficial for national economies. However, small enterprises often lack the financing and incentive for upgrading their manufacturing lines and need external support for the transitioning to a circular economy practices, reducing waste and making the manufacturing smart and flexible or for optimizing production processes. At the same time, for these small-scale factories the digital twin [3, 4] approach may show its efficiency providing real-time data on resource consumption and waste generation for analysis and informed decision-making to optimize performance and improve sustainability. Digital twins may become the driving force and an enabler for smart and sustainable manufacturing.

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2. Smart Manufacturing Optimisation in Food-Packaging Industry

One characteristic feature of digital twins, which are digital representations of physical elements, is the high connectivity of production equipment units. Digital twins make use of IoT sensors to monitor production lines in real time [5]. A food-packaging enterprise has been selected as a test-bed for this research (Figure 1). In the first stage, requirement elicitation has been done and domain-driven design [6] of the digital twin has been performed for the purpose of optimizing the manufacturing regimes. The factory already possesses a good level of digitisation, with energy consumption data, quality checks data and raw material usage data available for analysis. Present level of process automation can provide energy-efficient and on-time delivery of parts and products. However, there is no implemented decision-making system supporting fast responses of human operators to fluctuating market conditions and focused on reducing the energy consumption and raw material use optimization. Improvements of the manufacturing line performance and sustainability were identified as primary goals in implementation of the industrial digital twin. Development of the digital twin can allow nearly real-time and holistic assessment of the current energy consumption per unit of production at every stage of production cycle with factors affecting the productivity and energy consumption visualized. This may help the decision-maker not just to identify bottlenecks in production but also to simulate effects of changing regimes and take timely measures to mitigate risks. The nature of the production process, as can be ssen from Figure 1, requires participance of human operators in different sections of the manufacturing line. Coordinated actions of these operators need an intermediary digital platform, provided by the digital twin, to relieve humans of repetitive procedures control, allow them to focus on the decision making and creativity, let them promptly access the relevant information and reduce risk of human errors.

(**a**) (**b**)

Figure 1. Food packaging producer chosen as a use-case: (**a**) Manufacturing line for food packaging; (**b**) Food packaging device with QR code labeling.

In order to optimize manufacturing line performance we developed a model of material flow. Data on energy consumption, production, quality and efficiency are indispensable for analysis and allow smart sensors, meters, and other monitoring devices that will be connected to manufacturing machinery in order to identify the energy-intensive processes or equipment. The components of a smart manufacturing line can provide a variety of data summarized in Table 1. Properly performed data engineering (data collection, storage, and preparation) is a necessary prerequisite for a better understanding of the data collected [7-9].

For smart manufacturing processes and units it is necessary to develop a model that represents the current state of the production line. The digital twin platform can process data on-site or broadcast data to cloud services [4, 5] to support decision-making based on mathematical models characterizing resource consumption and process output quality and quantity.

Table 1
Data types, relevant for the industrial data platform in food packaging.

Decision-making level	Production process level	Data type
Production data	Production process data	Resource consumption data Quality checks data Emission and waste production data
	Equipment status data	Operating mode data Failures and downtime data
Energy consumption data	Grig electricity consumption data	Consumed power Seasonal variations
	Renewable power consumption	Consumed power Seasonal variations
Environmental data	Factory floor data	Temperature
	Surrounding area data	Humidity Air pollution

To determine the most efficient and feasible solution, several production regimes can be simulated using the digital twin. Digital twin simulates the behavior of the machine in order to predict potential problems and optimize the manufacturing processes and maintenance but also can trigger edge-system controls in case of malfunctions. For a specific processing stage, a set of parameters is to be prioritized in order to have sufficient amount of relevant information.

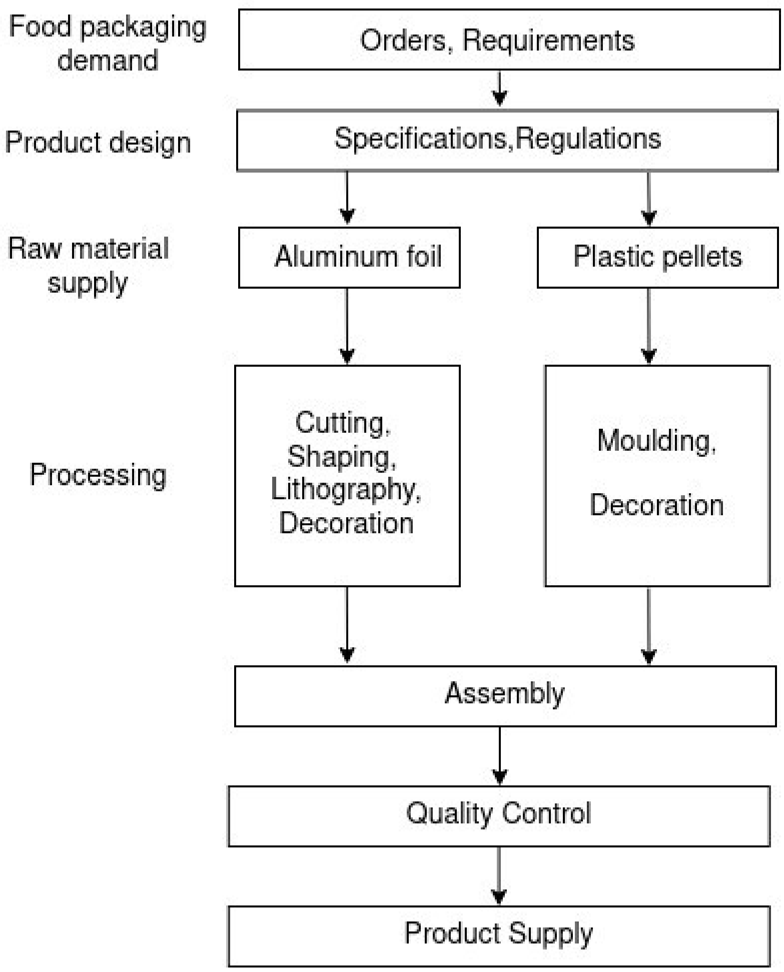

Figure 2. Product lifecycle stages controlled by the food packaging manufacturer.

By implementing a digital twin, it is possible to ensure that consistent and accurate data obtained from the sensors can enable real-time monitoring and analysis of a manufacturing facility's performance and energy consumption to optimize processes for a more sustainable lifecycle [10-11].

3. Smart Manufacturing Optimisation in Food-Packaging Industry

Based on the data obtained from the manufacturing line, a reference matrix would be developed consisting of the set of minimum parameters needed to mathematically describe each process and its dependencies, limits and boundary conditions. This would serve as a blueprint for further analysis and finding areas and methods for energy optimization and control. Target functions built on this dataset would be defined for each process that would serve as a tool for optimization of the process and effectively the entire system. The optimization diagram shown in Figure 3 illustrates a general approach that can help solve the optimization problem effectively. The inputs x and the outputs y are quantitative characteristics of the material and information flows that the production system receives from external entity and sends respectively to the same or different external entity.

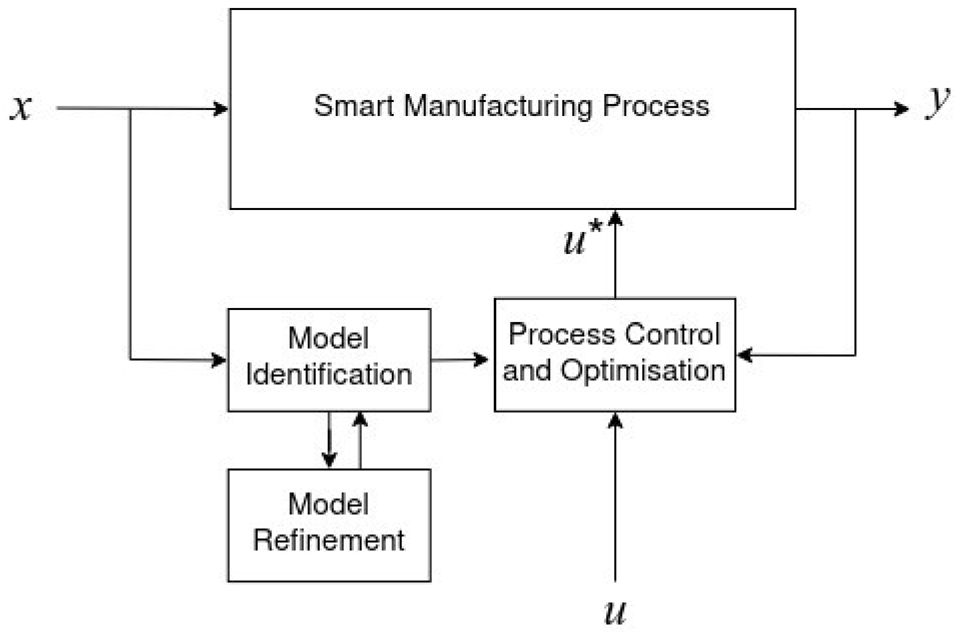

Figure 3. Optimisation diagram for the manufacturing process.

The optimal control signal u^* is a solution to an optimization problem to achieve the goals of a particular smart manufacturing use case. This optimal u^* should be obtained according to the method described in this section (examples of individual use cases are presented elsewhere) to improve the initial control signal u based on the model process description and standard methods. The peculiarity of the proposed approach is the improvement of the model, which is an integral part of solving optimization problems.

The general optimization problem involves functional relations of various types for a wide range of variables, making it very difficult to solve. The optimization recipe can be created as a superposition of partial solutions for different subsystems and the equations describing specific processes only contain variables of that subsubsystem (for discussion on this approach applicability see [3, 4]). Additionally, this strategy significantly lowers the optimization engine's processing power needs. The optimal solution for the particular subsystem may also be inconsistent with the key performance indicators of the entire system if various partial optimization problems are self-contained, which may be the case with distributed manufacturing systems. As a result, no decisions can be made and no corrective actions can take place until the full optimization solution is discovered for all systems at once.

Process state vector $\vec{x}=(x_1 x_2 \cdots x_n)$ and control vector $\vec{u}=(u_1 u_2 \cdots u_n)$ are tuned with the measured perturbations to choose the model and refine it. The optimization problem $max \sum_{i=1}^{N} F_i(\vec{x}_i, \vec{u}_i)$ at conditions $\vec{x}_i = \sum_{j=1}^{N} c_{ij} \vec{y}_j$, $\vec{y}_j = \vec{f}_i(\vec{x}_i, \vec{u}_i)$, for variable control vectors $\vec{u}_i$, input vectors $\vec{x}_i$, output vectors $\vec{y}_i$ related by the matrix c_{ij} for all subsystems.

4. Results and Discussion

In a general case, the fine optimization result is quite difficult to obtain. However, as the equation for i^{th} subsystem contains only the variables for this subsystem, the decomposition of the problem is quite straightforward and the overall control vector can be constructed as the cross-product of partial control vectors for all individual subsystems. The decomposition [12, 13] of the general process onto the component subprocesses allows to tackle problems of lower dimensionality either ignoring mutual influences or taking these into account as perturbations. Hierarchical approaches to optimisation problem may be applied for the optimal control of quasistatic processes. With decomposition onto N partial processes every individual problem is specified by its on equation of state $g_i(x_i, u_i, \pi_i)=0$, $i=1,2 \cdots N$. Vectors π_i contain relations for the constituent subsystems and may be approximated as linear $\pi_i = \sum_{j=1}^{N} C_{ij} x_j$. Then the general target function is represented by the decomposition $f(X, U) = \sum_{i=1}^{N} f_i(x_i, u_i, \pi_i)$. The corresponding Lagrange polynomial for i^{th} subsystem has the form

$$R(x_i, u_i, \pi_i, \lambda_i, \mu_i) = \sum_{i=1}^{N} f_i(x_i, u_i, \pi_i) + \sum_{i=1}^{N} \mu_i^T \left(\pi_i - \sum_{j=1}^{N} C_{ij} x_J + \sum_{i=1}^{N} \lambda_i^T g_i(x_i, u_i, \pi_i) \right). \quad (1)$$

First-order optimality conditions read as

$$\frac{\partial R}{\partial x_i} = \frac{\partial f_i}{\partial x_i} + \lambda_i \frac{\partial g_i}{\partial x_i}^T - \sum_{j=1}^{N} C_{ij}^T \mu_J = 0, \quad (2)$$

$$\frac{\partial R}{\partial \pi_i} = \frac{\partial f_i}{\partial \pi_i} + \lambda_i \frac{\partial g_i}{\partial \pi_i}^T + \mu_i = 0, \quad (3)$$

$$\frac{\partial R}{\partial u_i} = \frac{\partial f_i}{\partial u_i} + \lambda_i \frac{\partial g_i}{\partial u_i}^T = 0, \quad (4)$$

$$\frac{\partial R}{\partial \lambda_i} = g_i(x_i, u_i, \pi_i) = 0 \quad (5)$$

$$\frac{\partial R}{\partial \mu_i} = \pi_i - \sum_{j=1}^{N} C_{ij}^T x_J = 0 \quad (6)$$

and the system of equation (2)-(6) is solved with the corrected parameters iteratively. The iterative procedure is interrupted when the desired tolerance is reached. This method is suitable for on-line regime due to the possibility of interruption in arbitrary approximation and the obtained sub-optimal solution is nevertheless better compared to the previous one. Thus the general optimisation problem may be reduced to independent partial problems with π_i, $i=1,2 \cdots N$, containing only the variables for the partial problems b_i, and global variables a, identified by the supervisor. Tuning of the partial problem variables to the coordinator variables a, and identification of the partial problems is to be done in such a way that for a certain value $a = a*$ solutions of the partial problems correspond to the initial state of the global problem.

The hierarchical optimization is performed as a sequence of the following steps:

a) The initial value $a^{(0)}$ is chosen and the iteration counter $l = 0$ is set.

b) Independent partial problems are solved to determine the local variable value b_i^l at given $a^{(l)}$. Solving these partial problems may be parallelized in time.

c) Value $a^{(l+1)}$ is reset with new b_i^l, $i=1,2\cdots N$.

d) If $a^{(l)} \approx a^*$, the process is interrupted.

f) $l = l+1$, and control is transferred to step (b).

The coordination procedure is the most effectively used for the model in which the number of relevant variables is greatly reduced by choosing only the most important ones for a defined goal of the manufacturing transformation, for example, energy consumption and the recycling rate. Consider *X* to be the coordinator of the partial subsystems. The state variables relevant for the relations are to be put into the coordinating vector, other state variables can be inserted only into the partial problem vectors. This way the Lagrangian $R(x_i, u_i, \pi_i, \lambda_i, \mu_i)$ is composed of the partial functions

$$R_i(a, b_i) = f_i(x_i, u_i, \pi_i) + \mu_i^T \left(\pi_i - \sum_{j=1}^{N} C_{ij} x_J + \lambda_i^T g_i(x_i, u_i, \pi_i) \right), \tag{7}$$

where from the next *N* partial problems are obtained. For the fixed *X* the minimization with respect to u_i, π_i is performed with optimality conditions of the first order $g_i(x_i, u_i, \pi_i) = 0$ and $\pi_i - \sum_{j=1}^{N} C_{ij}^T x_J = 0$.

One can fulfill the condition $\frac{\partial R}{\partial x_i} = 0$ by resetting the coordinator variables:

$$x^{(l+1)} = x^{(l)} - \alpha \left(\frac{df}{dx} + \lambda \frac{dg^T}{dx} - \mu C \right)^{(l)}, \tag{8}$$

where α is the chosen step magnitude. This equation provides the Lagrange minimization by sequential resolution of the above equations with interruption condition $\left| x^{(l+1)} - x^{(l)} \right| < \varepsilon$, for the desired tolerance ε that guarantees practical problem solvability.

Using production data from the pilot food-packaging facility, the solution of the partial problem for the most energy consuming and quality-critical part, which is the forming press, has been attempted to test the proposed methodology. This allowed identifying the optimal maintenance regime for particular regimes of the production line, determined by the external demand. Optimization has been done in two input parameters, which are quantity of the raw material (plastic sheet) per hundred units of product (x_1) and energy used by the forming press (x_2). Output parameters for the target function minimization were the percentage of quality products (y_1) and the combined production cost and energy consumption parameter (y_2), both of which are directly related with the sustainability goals. Controls were specified as maintenance duty cycle (u_1) and seasonality of energy consumption (u_2), which is related to availability of the renewable energy for the manufacturing line.

Numerical results show that the decomposition allows to drastically reduce the problem dimensionality thus reducing requirements to the processing power of edge devices which would be able to perform the needed calculations. This way the partial optimization problems with short time cycle can be assigned to the low-resource edge devices which receive streaming data on product fast quality checks, which are performed at every production stage as well as data about availability of the renewable (for example, solar) energy. Only the optimization of long-term regimes of the production line will be escalated to the high-performance processing units (cloud infrastructure), which will also reduce the information security risks.

5. Conclusions

Wide adoption of digital platforms may lead to novel collaborative business models promoting sustainable development. A generic model of product lifecycle in the packaging industry is considered and the procedure of the production optimisation is proposed, which reqiures specific chouice of the terget function. For the particular case of food-packaging manufacture, the target function has been built with the overall goal of reducing energy consumption and optimizing the use of raw material. By prioretizing the desired effects of the production optimization, we make it possible to split the general model into composite blocks aith their corresponding variable sets. This dimensionality reduction significantly simplifies data processing thus ensuring that the digital twin design allows taking timely and efficient decisions regarding the manufacturing process.

Among benefits from the proper decomposition of the model we stress the ability to balance needs of on-site processing for fast decision-making and proper operation control which importance is exemplified by the packaging industry use-case. By minimizing the target function on the parameters of product quality and energy consumption, the smart manufacturing facility simultaneously improves performance and contributes to the goals of sustainable development. The loss of some information which may be useful in other respects, like predictive maintenance, may be regarded as disadvantage of this type of system decomposition, however, properly designed digital data platform may compensate for such loss and allow failure risk mitigation by storing extra information in external datalake for separate processing, which will be discussed elsewhere.

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