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IDENTIFICATION OF INFLUENCE OF DIGITAL TWIN TECHNOLOGIES ON PRODUCTION SYSTEMS: A RETURN ON INVESTMENT-BASED APPROACH

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The object of this study is the impact of different digital twin solutions on the performance of job-shop manufacturing systems, while economic aspects are also taken into consideration. This paper proposes an approach to analyze the impact of different identification systems on the efficiency and ROI of digital twin deployment in production systems. In order to achieve this aim, let's analyze the investment and operation cost of different Internet of Things technologies. The next phase of the research work was the definition of performance parameters, which makes it possible to analyze the impact of different digital twin solutions on the productivity of the job-shop manufacturing system. It is possible to choose four financial indicators to analyze the economic impact of digital twin solution on job-shop manufacturing: return on investment, compound annual growth rate, internal rate of return and net present value. Our approach is based on a novel agent-based simulation model using AnyLogic simulation tool. From the results of this productivity analyses, the model computes the financial indicators, which describe the expected financial impact of the investment and operation cost. It is compared the impact of barcodes and radiofrequency identification technologies on the financial and technological impact of the job-shop manufacturing environment. The numerical analysis of a job-shop manufacturing system shows, that the radiofrequency identification-based digital twin solution has 9.2 % higher return on investment, 53 % higher net present value and 1.6 % higher compound annual growth rate. The model can be easily converted to analyze other types of manufacturing systems, which can lead to increased efficiency of digital twin solutions

Keywords: digital twin, barcode technology, radiofrequency identification, agent-based simulation, financial evaluation

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1. Introduction

The Fourth Industrial Revolution, the digitalization, the outbreak and spread of COVID-19 led to the increase of importance of digital twin solutions. The MarketsandMarkets portal forecasted, that the digital twin market would reach a 73.5 billion USD Compound Annual Growth Rate (CAGR) by 2027. As the report emphasizes, the main players in the digital twin market are the following companies: General Electric, Microsoft, Siemens, Amazon, Ansys, Dassault Systemes and PTC [1], and these companies will significantly revolutionize the processes in industry, agriculture, civil engineering, healthcare and services.

Digital Twin technology can be defined as an integration of data between a real world object or system and a virtual, digital object or system.

It is possible to find a wide range of digital twin definitions in [2]. The first definition by NASA focusing on aerospace industry is the following [3]: "A Digital Twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.", which defines the digital twin for the whole lifecycle of general objects, processes and systems: "A Digital Twin is a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle."

In the literature, it is possible to find misconceptions, which define digital solutions as digital twin, but it is important to define, that in a digital twin the data exchange is automatized in both directions between the real world system and the digital twin (Fig. 1).

In the case of a digital model, the data exchange is manual in both directions. An example of a digital model is a digital design of a building or a product. It is about a digital model in this case because after the digital model is created, if there is a change in the physical part, it does not affect the digital model. The same is true in the other direction, changes in the 3D model do not result a direct change in the modelled part. It is possible to build a link between the physical part and the CAD model using for example a 3D metrology (e. g. GOM by Zeiss), but this link can be described as a digital model until there are not direct links between the real world model and the virtual model. In the case of a digital shadow, the data exchange is automatized from the real world model to the digital twin, while it is manual from the digital twin to the real world system.

The digital twin application can integrate a wide range of state of the art technologies, therefore it is important to find the most suitable, cost efficient solutions. As Fig. 2 shows, these technologies can be combined in different application field, where cyber-security, integrity, infrastructure and standardization related problems have to be solved.

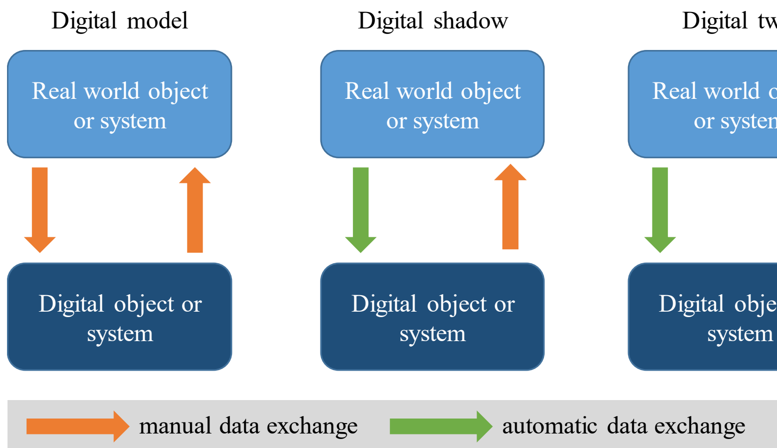


Fig. 1. Data exchange in digital model, digital shadow and digital twin [4]

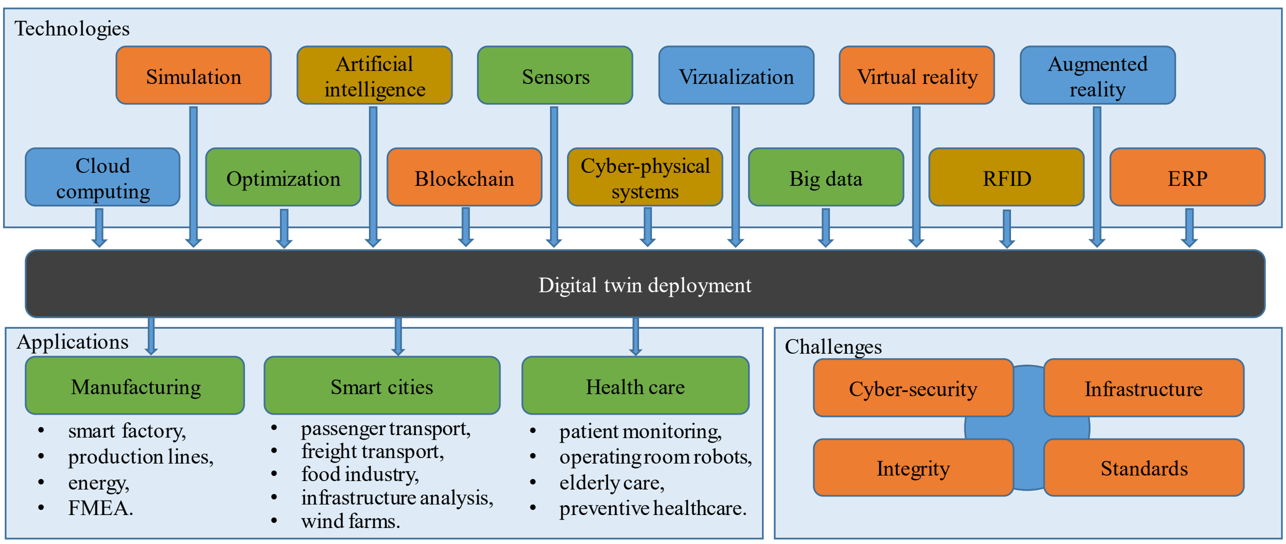


Fig. 2. Technologies, applications and challenges of digital twin deployment

One of the most important achievement of a digital twin deployment project is to estimate the financial impact of the investment. A wide range of articles discusses the positive impact of digital twin applications in the field of automotive industry [5], food industry [6], agriculture [7], health care [8], logistics [9], facility management [10], but these researches are generally focusing on the performance indicators (lead time, efficiency, availability, capacity utilization, flexibility, productivity) and only a few of them analysis the financial impact. Based on this fact, research on the financial evaluation of Industry 4.0 technologies is important, especially in the case of expensive, integrated technological solutions, such as digital twin, where a wide range of state of the art technologies are applied to improve the flexibility and productivity of production systems.

2. Literature review and problem statement

There is a wide range of practical applications of digital twin solutions, integrating Industry 4.0 technologies to achieve significant economic impact. Facility and building management, health care, maintenance, product design, system control, asset monitoring and manufacturing represent these application fields. The first important phase of digital twin deployment was the automation, Internet of Things solutions and mobile applications. In the field of building and facility management, Building Automation Systems (BAS) and Building Information Modeling (BIM) [11] have extended these technologies. Beyond this, the digital twin can support an efficient facility management, as the efficient data collection and processing can provide significant economic benefits even in the early stages of facility operation. In a natural gas production plant, an online digital twin was used to increase the output of saleable products and reduce energy consumption and emissions. The paper [12] presents the results of research to highlight the main advantages of the digital twin deployment including the true representation of the physical processes of the plant, dynamic monitoring and calculation of energy-related key performance indicators, forecasting of lifecycle of technological resources using machine learning, but there were unresolved issues related to the financial impact of digital twin with. The reason for this may be that the article mentions an increased revenue and an attractive return on investment, but a deeper analytical or simulation-based approach could validate these financial impacts. The same topic is also discussed in the oil and gas industry, focusing on the improvement of management of 200 drilling rigs and 300 completion wells in an oil field [13]. This research emphasizes the importance of real-time big data solutions. Digital twin technologies were used in the Field Development Process (FDP) of petroleum industry to improve the financial impact of investments. This approach tries to convert the digital twin deployment into financial indicators [14]. Digital twin deployment can also support measuring bridge condition performance state. It is especially important from financial point of view, because budget decisions require quantitative information, which is not always available by visual inspection of bridge assets. As the cloud-based Internet of Things Platform deployment shows, the costs of the asset management of bridges can be significantly decreased through digital twin. The financial analysis of digital twin deployment shows, that smart bridges show a high ROI from performance monitoring [15]. This financial analysis resulted measurable financial impact, but these impacts are static. A way to overcome these difficulties can be the application of a simulation-based approach, which makes it possible to analyze the financial impact in the case of different scenarios, depending on the lifecycle of the technological system. The application fields of digital twin includes both industrial and agricultural examples. Plant growth and plant cultivation in rice fields can be monitored and influenced by a digital twin using ontology-based knowledge base to perform adaptive scheduling of resources, such as fertilizers, protection agents, vehicles and human resources [16]. As an example of executable digital twin (xDT) in the food industry shows, one of the main problems of digital twin applications is that they cannot be deployed at the operational level of food processing technologies, because they are extremely complex to react real-time. These problems can be solved using Industry 4.0 technologies integrating machine-learning technologies for online quality predictions and predictive maintenance scheduling based on fast edge computing to collect sensor data for the xDT [17]. These research results are analyzing the technological impacts of digital twin solutions focusing on overall equipment effectiveness (OEE), shown, that xDT can significantly increase the performance of the technological system, but the financial impact of xDT application should have a deeper analysis, which can be based on simulation supported methodologies. The aggregation level of many types of data significantly influences an example in the semiconductor device manufacturing shows, the return of investment of factory scheduling, which is an integrity-related topic of big data [18]. Technologies like cloud computing, simulation, optimization, artificial intelligence, blockchain, smart sensors, cyber-physical systems, additive manufacturing, robotics, visualization, quantum computing, big data, virtual and augmented reality, Internet of Things (IoT), nanotechnology, radiofrequency identification, autonomous vehicles and machine learning are under the umbrella of Industry 4.0 solutions and these technologies can be used to integrate technological, human and logistics resources into a cloud [19]. In the field of city logistics, the most important initiative is to build sustainable smart energy cities (SECs). However, independent products and unit technologies are available for SECs, but it is not possible to build efficient solutions without a proper connection of these unit technologies, therefore the architecture of different IoT solutions become more and more important. The paper [20] presents the results of research on the integration of IoT technologies, shown, that an AI-based physical and virtual platform using a multi-layer architecture could be suitable for the integration of the available I4.0 technologies, but the financial impact of these integration potentials is not deeply analyzed. This issue can be resolved using economic analysis, which could support decision making while planning IoT solutions in manufacturing processes.

A wide range of researches has discussed the main streamlines of digital twin solutions, the potential architectures, the standardization problems, optimization algorithms and integration aspects, but only a few of them tries to define the estimated economic impact.

The theories and methods of complexity science must play an important role in the design and operation of digital twin supported systems [21]. This complexity is resulted by the complex set of equipment, software, investment and organization.

A wide range of multi-scale, multi-scenario, multi-dimensional applications of digital twin are existing, which can be defined as complex digital twin [22], and it is not easy to model, design, build, operate and maintain their components and the whole system. Therefore, it is essential to research the financial impact of digital twin solutions.

All this suggests that it is advisable to conduct a study on analysis of different digital twin applications regarding technological, logistics and economic impact. Within the frame of this research work, the authors discuss a simulation-based approach, which can be used to define the return of investment and the net present value of digital twin deployment focusing on job-shop manufacturing system. This article focuses on the simulation-based analysis of the impact of digital twin deployment in the case of a job shop manufacturing system.

3. The aim and the objectives of the study

The aim of this research work is to identify the impact of digital twin solutions on the efficiency of job-shop manufacturing using agent-based simulation.

To achieve this aim, the following objectives are accomplished:

– identify the physical and digital resources of the digital twin supported job-shop manufacturing;

– identify the most important performance indicators to measure the impact if digital twin solution on the performance of the job-shop manufacturing;

– define the most important financial indicators to measure the financial impact of different digital twin solutions focusing on identification technologies (barcode and RFID);

– perform an agent-based simulation of digital twin supported job-shop manufacturing and integrate a financial evaluation module into the agent-based simulation to link the productivity and the financial indicators;

– analyze the impact of different digital twin solutions on the productivity of job-shop manufacturing.

4. Materials and methods

The object of this research is to impact of digital twin solution using different identification technologies on the performance and economic parameters in job-shop manufacturing systems. The main hypothesis of the study is that digital twin solutions can significantly increase the performance of job-shop production systems, but the economic impact of digital twin solutions must be analyzed to validate the advantages of digital win solutions. Our assumption is that the financial impact of different digital twin solutions is influenced by the used Industry 4.0 technologies, therefore the financial impact must be analyzed in different cases of digital twin solutions. In this study, let's focus on identification technologies, which is a simplification, because it is also possible to take other IoT technologies into consideration, but it can be a future research direction.

Our simulation-based evaluation approach has the following main phases (Fig. 3):

– definition of the architecture;

– analysis of the technological units, solutions of the potential digital twin solutions to identify the main cost components (sensors, actuators, architecture, network, software, database, cyber-security);

– identification of the main potential performance-related impacts of the digital twin to identify the main factors of expected cost reduction (lead time, capacity utilization, productivity, flexibility, efficiency);

– definition of the main investment indicators to measure the financial impact of the digital twin (Net Present Value, Internal Rate of Return, Return on Investment, Compound Annual Growth Rate);

– building of the agent-based simulation model of the job-shop manufacturing system in the case of both conventional and digital-twin supported operation;

– computation of the financial impact of digital twin deployment through different scenario analyses.

This research is based on the authors earlier research results [23], where the economic impact of digital twin technology was analyzed by evaluating the digital twin investment on the basis of productivity indicators obtained by agent-based simulation using a suitable Excel spreadsheet. In this article, the evaluation based on this Excel spreadsheet was integrated into the agent-based simulation method, so that the simulation of the job-shop production system calculates the financial indicators for a given time interval in real time.

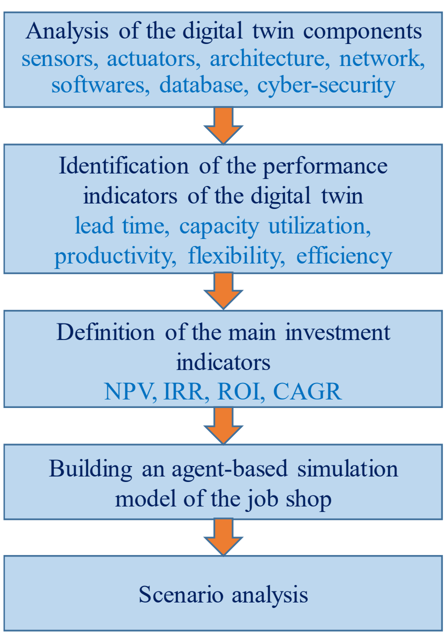


Fig. 3. Flowchart of the evaluation process

The application of these phases makes it possible to analyse the impact of different types of digital twin solutions on the efficiancy of production systems and compute the expected finanacial impacts.

5. Results of simulation-based evaluation of the impact of digital twin

5. 1. Analysis of the digital twin components

The digital twin solutions integrate a wide range of technologies including hardware and software components. A digital twin is a digital representation of a physical system or object, where the data flow between the digital and the real world system or object is fully automatized. As a simple model, it is possible to say, that sensors collect status information in the real world system and transfer these data to the digital representation, where a decision support system makes decisions regarding the operation of the physical system, and these decisions are transferred as control data to the actuators of the physical system. The dashboard makes it possible to perform human-machine interaction through a special graphical user interface (GUI) focusing on the key performance indicators (KPIs) of the physical system (Fig. 4).

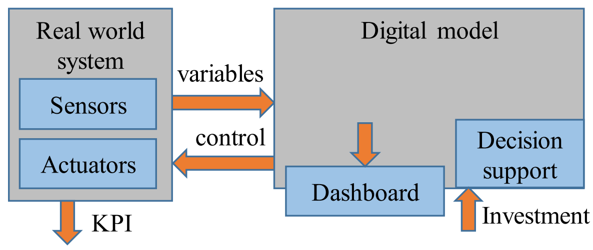


Fig. 4. Technologies, applications and challenges of digital twin deployment

If it is necessary to analyze the impact of digital twin deployment on the financial indicators of the real-world system, then it is necessary to define the main components of the digital twin, which includes sensors, actuators, architecture, network, software, database, cyber-security. These technology units can be defined as shown in Fig. 5.

The real-world system includes processes of the value chain and the required resources of technology, logistics and human operators. The link between the real world system and the digital twin is performed through sensors and actuators. Sensors upload process parameters to the data base and the decisions made by the digital twin are performed by actuators connected to the technological and logistics resources of the job-shop manufacturing. The identification and the tracking of products and processes can be performed using different identification technologies including barcode and RFID. The layout of the job-shop manufacturing plant, the technological and logistics processes and the products are defined by the Enterprise Resource Planning (ERP) and the Manufacturing Execution System (MES) [24]. The database integrates both the data from the real world system and the digital system. The digital twin uses a dynamic simulation model to analyze the operation of the real worlds system and forecast the potential future states of the real world system. The simulation model is permanently upgraded by the sensor data collected from the real world system, therefore the simulation model reflects the current status of the job-shop and this current status can also be transferred to the ERP and MES. The decision making process is supported by a dashboard, which is a GUI including human-machine interaction module and visualization of KPIs, such as lead time, productivity, inventory, capacity utilization, idle time of technological and logistics resources and operation costs.

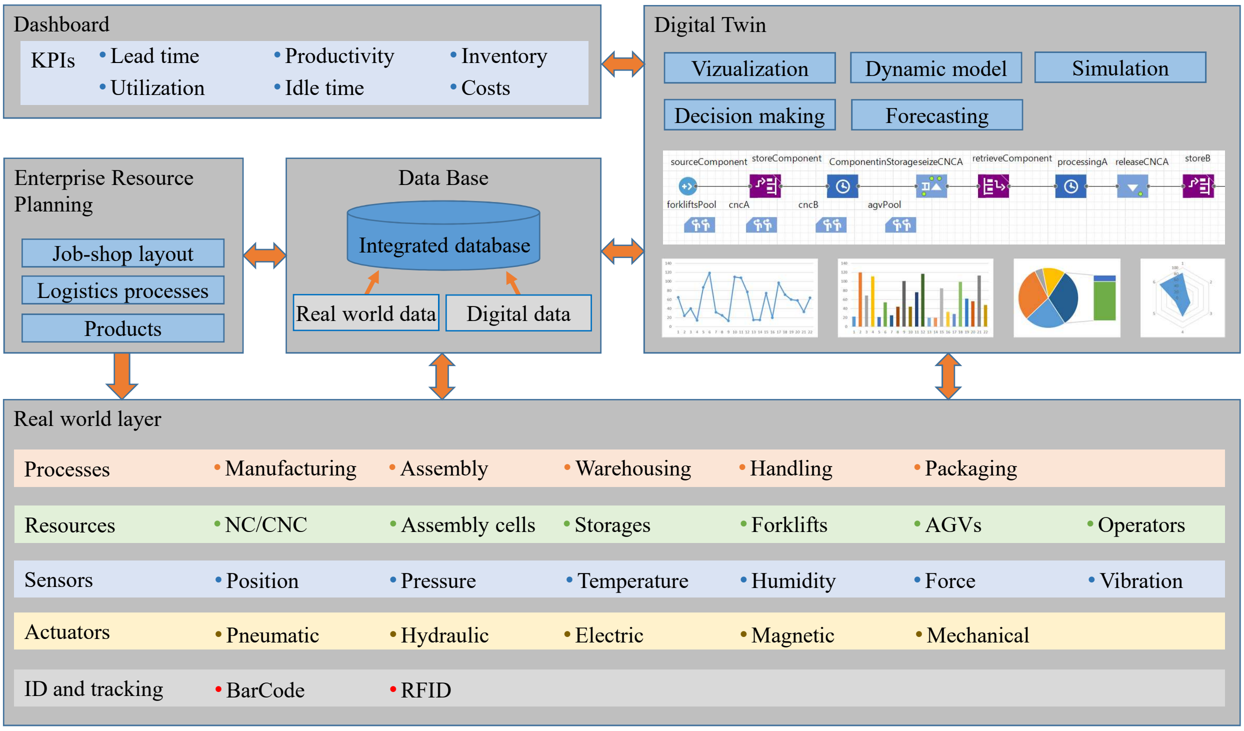


Fig. 5. Conceptual framework of the digital twin deployment of job-shop manufacturing system

The investment cost of a digital solution includes the deployment cost of sensors, actuators, network, software, database and cyber-security. The main components of the digital twin solutions can be summarized as shown in Table 1.

Table 1

Components of the digital twin solutions

Component type	Typical solutions and apps
Sensors	Proximity, motion, occupancy, optical, temperature, humidity, etc.
Actors	Hydraulic, pneumatic, electric, thermal, magnetic, mechanical, etc.
Network	Wi-Fi, Bluetooth, NFC, LPWAN, cellular network
Database	Centralised, distributed, NoSQL, relational, cloud, network, object-oriented, hierarchical [25]
Application server	Jboss, Weblogic, Websphere, Glassfish, Tcat Server, Apache Geronimo, Jrun, Oracle OC4J, SAP Netweaver AS [26]
Security	Firewalls, endpoint detection and response, antivirus software, email protection, two factor identification, hardware security key
Control or monitor application	Input control, output control, processing control, access control, integrity control [27]
Identification	Barcode, RFID

However, the sensors used in IoT solutions (proximity, motion, occupancy, optical, temperature, humidity, etc.) become more and more cheaper [28], but it is only true in the case of low-cost sensors. In the case of low-cost sensors, it is about prices below 0.5 USD per pieces, but in the case of professional sensor with high sensitivity and high availability the prices are more higher.

The actuators are expensive parts of real world systems, for example in the case of manufacturing systems, where the actuators of NC and CNC machines and the actuators of automatized material handling machines and systems are about 10-3000 USD per pieces and this price depends on the type of the actuator (hydraulic, pneumatic, electric, thermal, magnetic, mechanical, etc.).

The network cost of an IoT solution depends on the type of the connection. Short range wireless (Wi-Fi, Bluetooth, NFC), low power wide area network (LPWAN) and cellular solutions can be taken as potential solutions into consideration. In the case of cellular network, it is about a 0.04 USD per MB networking cost, but embedded software cost must be also taken into consideration with a 10000 to 30000 USD cost [29].

The estimation of database cost is a complex problem, because there is a wide range of costs to be taken into consideration including storage cost, usage cost, read and write operation cost. As an example [30], the cost comparison between Google Cloud Bigtable and Amazon DynamoDB shows a significant difference between capacity and usage cost (3164 USD per month total cost for Google Cloud Bigtable and 11353 USD per month total cost for Amazon DynamoDB).

The cyber-security solutions are generally focusing on protection against ransomware, data breaches, phishing attacks, DNS hijacking, crypto-jacking, insider threats and denial of service attacks. The costs of cyber-security are significantly influenced by the size of the company, types and sensitivity of data, related services and they can be defined within the following cost ranges [31]:

– firewalls with professional configuration and subscription: 1500-15000 USD;

– endpoint detection and response: 5–8 USD per user per month and 9–18 USD per server per month;

– antivirus software: 3–5 USD per user per month and 5–8 USD per server per month, monitoring 100–2000 USD per month;

– email protection: 3–6 USD per user per month,

– two-factor authentication: <10 USD per user per month,

– hardware security key: 30–60 USD per pieces.

As the above-mentioned costs of the components of an IoT solution shows, the estimation of the investment and operation costs of a digital twin deployment is a very complex problem because the cost estimation is significantly influenced by the components used, size and type of data, connected services.

5. 2. Identification of the performance indicators of the digital twin deployment

Within the frame of our approach, a wide range of performance can be taken into consideration to measure the impact of the digital twin deployment on the job-shop manufacturing system. These performance indicators are the followings:

– number of produced items: this performance indicator can be used to measure the fulfillment rate of customers' demands;

– number of working hours: this performance indicator can be used to measure the capacity utilization of resources;

– error rate or inaccuracy: this performance rate can be used to measure the quality of manufacturing processes, for example the impact of using different identification solutions we can avoid inaccuracy caused by misidentification;

– failure in the production system: this performance indicator can reflect the quality of monitoring of the manufacturing process and resources, for example the digital twin deployment makes the real-time continuous monitoring of the manufacturing system and the forecasting of the future status of its resources;

– number of not produced items: this performance indicator can be used to measure the fulfillment rate of customers' demands;

– utilization of manufacturing, material handling and human resources: this performance indicator shows the quality of process control;

– inventory level and inventory cost: this performance indicator can evaluate the material handling operations including purchasing, warehousing and distribution processes;

– manufacturing cost: this performance indicator reflects the performance of manufacturing operations;

– materials handling cost: this performance indicator reflects the performance of logistics operations.

These performance indicators make it possible to measure the impact of the digital twin application on the job-shop manufacturing system.

5. 3. Investment indicators

Within the frame of our approach, let's use the following four financial indicators to evaluate the financial impact of the digital twin deployment: Return on Investment, Net Present Value, Internal Rate of Return and Compound Annual Growth Rate as follows.

Return on Investment. The Return on Investment reflects the profitability of an investment depending on the final value of the investment and the cost of investment as follows:

$$ROI = \frac{FVI - IVI}{CI}, \tag{1}$$

where ROI is the Return on Investment, FVI is the final value of the investment (analyzed system), IVI is the initial value of the investment, and CI is the cost of the investment.

Net Present Value. The Net Present Value represents the current value of the future stream of payments from the company for the digital twin deployment depending on the discount rate, number of time periods, cash flow and initial investment, and it can be calculated in the case of a long-term digital twin deployment project as follows [32]:

$$NPV = \sum_{t=0}^{T} \frac{CI - CO}{(1+d)^t} - I, \tag{2}$$

where NPV is the net present value, CI is the net cash inflow within a time period, CO is the net cash outflow within a time period, d is the discount rate influenced by either the cost of capital or the potential returns expected from other investments, T is the time period of the analysis and I is the initial investment. In this calculation, the net cash inflow and the net cash outflow are constant, because let's calculate with an average production intensity in the manufacturing system. Let's use CO in the calculation to taking the operation cost (label/tag costs) into consideration.

Internal Rate of Return: The Internal Rate of Return is the annual rate of growth that the digital twin deployment is expected to generate. The IRR can be calculated from the following equation:

$$\sum_{t=0}^{T} \frac{CI - CO}{(1+d)^t} - I = 0. \tag{3}$$

The calculation of IRR can help to analyze the impact of digital twin project and to determine the investment returns of different digital twin deployments based on available Industry 4.0 technologies.

Compound Annual Growth Rate: The Compound Annual Growth Rate represents the return on an investment over a certain period of time, but is can be calculated a more easier way than IRR as follows:

$$CAGR = \left(\frac{FV}{IV}\right)^{\frac{1}{T}} - 1, \tag{4}$$

where $CAGR$ is the Compound Annual Growth Rate, FV is the final value of the analyzed system, IV is the initial value of the analyzed system and T is the number of time periods to be taken into consideration.

5. 4. Agent-based simulation model of a job-shop

In the manufacturing processes let's define a huge number of types of manufacturing systems, but there are two main types of shops: flow-shop and job-shop. In the case of a flow-shop the manufacturing operations are ordered in a fixed linear structure. In a job-shop, the routing of operations of different items is flexible and it means, that all products to be manufactured can have individual manufacturing route.

Within the frame of our research, let's demonstrate our evaluation approach in the case of a job-shop manufacturing system. In our scenario, let's analyze a job-shop manufacturing system including 6 CNC drilling machine, 4 CNC milling machine, an input storage, an intermediate storage between the drilling and milling operations, and an output storage for the final products. The structure of this scenario is shown in Fig. 6.

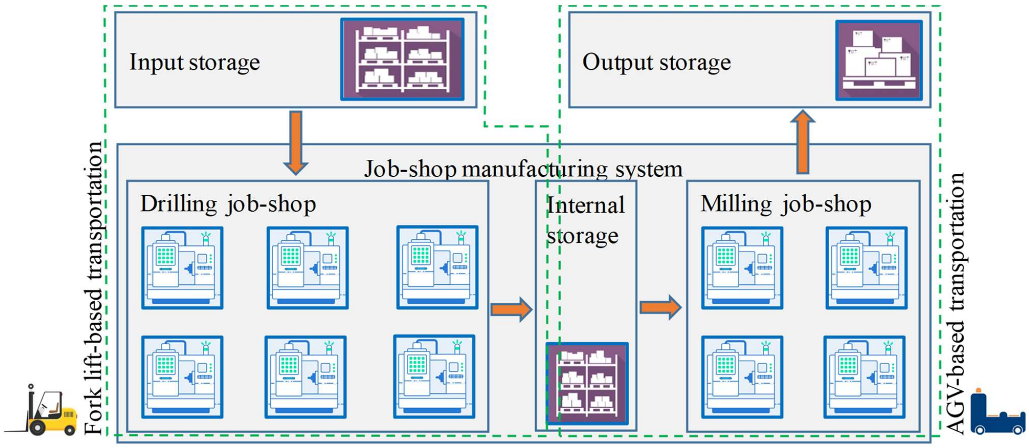


Fig. 6. Structure of the job-shop scenario

The first phase of model building is to define the layout of the job-shop manufacturing system including locations of milling and drilling machines, storages, forklift and AGV pools and transportation routes. The second phase of the model building is to define the main routes using point nodes, rectangular nodes and polygonal nodes. Point nodes were used to define the loading and unloading locations of drilling and milling CNC machines. Rectangular and polygonal nodes were used to define operation areas for AGV and forklift pools, input and output zones, as sources and sinks of the job-shop manufacturing system. After defining the point, rectangular and polygonal nodes the next step is to define transportation routes using the path function of the simulation software. Paths can be defined among nodes representing the connection points of manufacturing and materials handling resources to the transportation network.

The third phase of the model building is to define the physical objects (resources) of the job-shop manufacturing system. Let's use the AnyLogic multimethod simulation modelling tool to build the real-world system (Fig. 7) and define resources for transportation operations (AGV and ForkliftTruck), technological operations (CNCA and CNCB) and for components to be manufactured (Component).

The fourth phase of the model building is the definition of agents. Agents represent physical and logical things of systems. The definition of agents includes the following steps: define variables and events.

The agents for transportation processes are defined (agvPool, ManufForkliftPool, SinkagvPool, StorageForkliftPool), for storage processes (storeA, storeB and storeC), for technological resources (cncA and cncB), for initialization and closing of the analyzed process (sourceCom and sink), for storage process (CominStoA, CominStoB and CominStoC), for milling and drilling operations of CNCs (procA and procB), for seizing products between storages and machines (seizeCNCA and seizeCNCB) and for release CNC machines after operations (relCNCA and relCNCB). This defined simulation model makes it possible to perform the scenario analysis of the described job-shop manufacturing system using various parameters influenced by the type of the applied digital twin.

While running the simulation, it is possible to analyze the operation of agents (Fig. 8, *a*), the statistics of resources including utilization of capacity, currently active resources, total processed units (Fig. 8, *b*), the whole physical process in 3D visualization (Fig. 8, *b*) and other parameters, such as utilization or cost structure (Fig. 8, *c*).

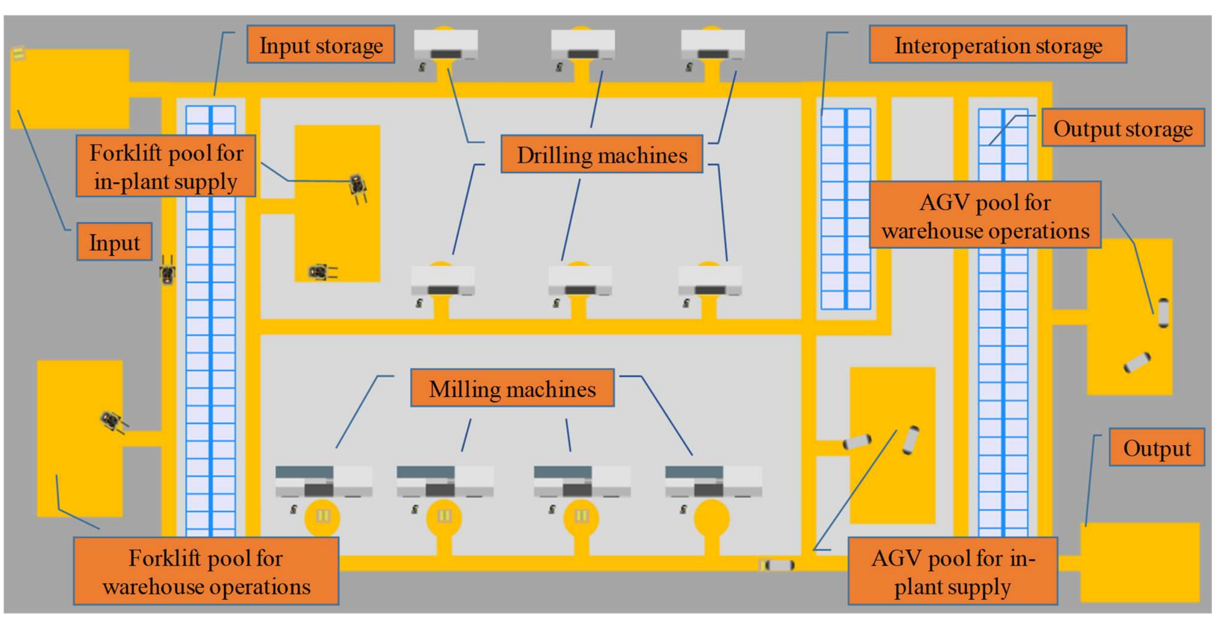
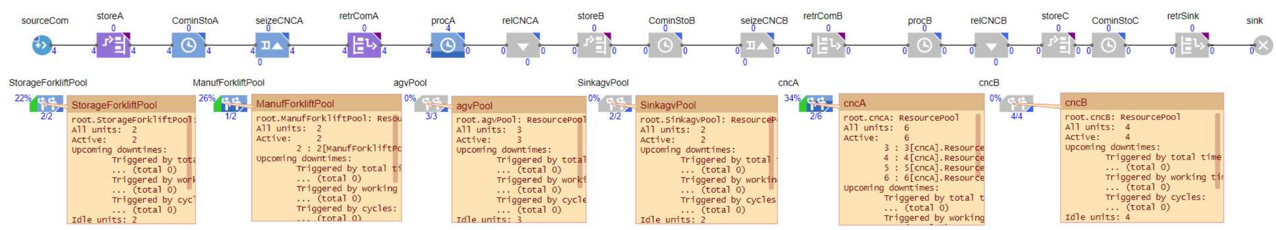
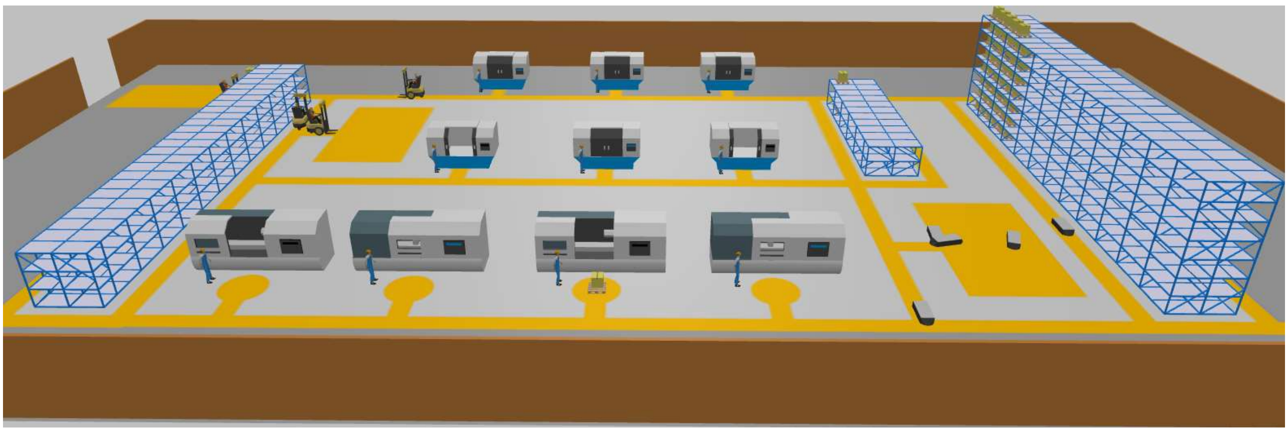


Fig. 7. The physical objects of the job-shop manufacturing system



a



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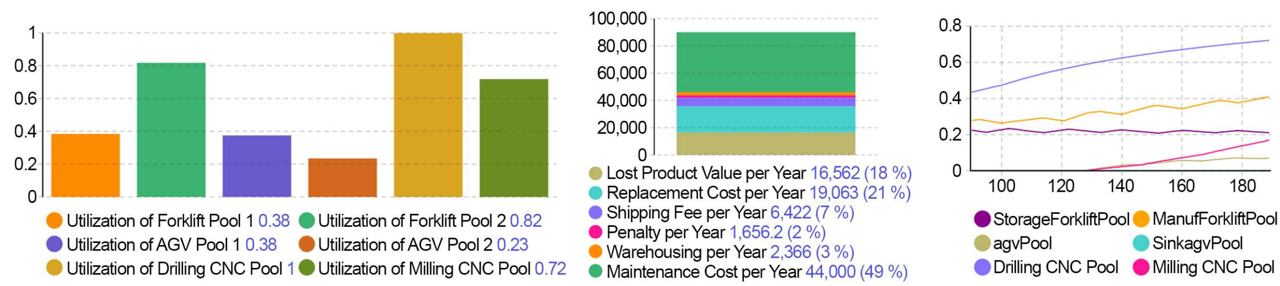


c

Fig. 8. Main parts of the simulation screen:
a – agents; *b* – resources and 3D animation; *c* – statistical analysis of the job-shop manufacturing system

As Fig. 8, *a* shows, in the case of the agents, the number of input and output objects are visualized real time, which makes it possible to identify deadlocks in the debugging phase of the model. The 3D animation is optional as shown in Fig. 8, *b*, it is possible to switch between 2D and 3D animation. One of the most useful part of the simulation software is the statistical analysis, as shown in Fig. 8, *c*, it is possible to add and configure a wide range of statistical tools writing Java Scripts.

5. 5. Numerical analysis

Within the frame of the numerical analysis, three different scenarios will be compared to show the financial impact of different digital twin solutions. The first scenario shows the costs of a conventional job-shop manufacturing system without digital twin deployment. In this scenario analyses the following parameters are given:

– n: daily number of items to be produced in pcs/day;
– w: number of working days per year in day/year;
– c^I: intrinsic cost per product in EUR/pcs;
– c^R: replacement cost per product in EUR/pcs;
– c^P: specific penalty cost per product in EUR/pcs;
– c^S: shipping fee per product in EUR/pcs;
– c^W: warehousing cost per product in EUR/pcs;
– c^M: average specific maintenance cost EUR/maintenance;
– I: planned yearly income from the supplier EUR/year.

In the conventional solution the inaccuracy of the manufacturing system is r_{INA}=2.50 %, while the failure in the manufacturing system is about f=3.75 %.

Based on these input parameters it is possible to calculate the following manufacturing – and logistics-related parameters of the job-shop manufacturing system:

– yearly number of items to be produced:

$$N = n \cdot w; \tag{5}$$

– yearly number of not produced items:

$$N^{NOT} = n \cdot f + (1-f) \cdot n \cdot r_{INA}; \tag{6}$$

– yearly lost product value:

$$v^{LOST} = N^{NOT} \cdot c^I; \tag{7}$$

– yearly replacement cost of lost products:

$$C^R = N^{NOT} \cdot c^R; \tag{8}$$

– yearly penalties to be paid due to the lost products to the buyer:

$$C^P = N^{NOT} \cdot c^P; \tag{9}$$

– yearly warehousing cost of products to be replaced:

$$C^W = N^{NOT} \cdot c^W; \tag{10}$$

– number of yearly required maintenances:

$$n^M = f \cdot 1000; \tag{11}$$

– yearly cost of maintenance:

$$C^M = c^M \cdot n^M. \tag{12}$$

Based on the above-mentioned parameters, the yearly profit of the conventional job-shop manufacturing system can be calculated as follows:

$$P_1 = I - v^{LOST} - C^R - C^P - C^W - C^M. \tag{13}$$

The above-mentioned calculations (5)–(13) are integrated into the simulation model as a Java script:

YearlyProducedItems=DailyProducedItems*WorkingDaysperYear;
YearlynotProducedItems=YearlyPlan–YearlyProducedItems;
LostProductValue=YearlynotProducedItems*IntrinsicCost;
ReplacementCost=SpecificReplacementCost*YearlynotProducedItems;
ShippingFee=SpecificShippingFee*YearlynotProducedItems;
Penalty=LostProductValue/SpecificPenalty;
WarehousingCost=YearlynotProducedItems*SpecificWarehousingCost;
MaintenanceCost=AverageMaintenanceCost*Number of Maintenances;
TotalCost=MaintenanceCost+WarehousingCost+Penalty+ShippingFee+ReplacementCost+LostProductValue;
ProfitUsingBarCode=InvestmentCost-TotalCost;
ReturnOnInvestment=(Year*(ProfitUsingBarCode–ProfitwithoutDigitalTwin)–(CostofDigitalTwinDeployment+Year*YearlyLabelCost))/(CostofDigitalTwinDeployment+Year*YearlyLabelCost);
NetPresentValue=(ProfitUsingBarCode–ProfitwithoutDigitalTwin-YearlyLabelCost)/pow(1+InterestRate,1)+ +(ProfitUsingBarCode–ProfitwithoutDigitalTwin-YearlyLabelCost)/pow(1+InterestRate,2)+(ProfitUsingBarCode–ProfitwithoutDigitalTwin-YearlyLabelCost)/pow(1+ +InterestRate,3)+(ProfitUsingBarCode–ProfitwithoutDigitalTwin–YearlyLabelCost)/pow(1+InterestRate,4)– –CostofDigitalTwinDeployment;
CompoundAnnualGrowthRate=pow(ProfitUsingBarCode/ProfitwithoutDigitalTwin,1/Year)-1.

The input parameters and the computed indicators regarding financial parameters of the simulation model of the conventional job-shop without identification technology are shown in Fig. 9.

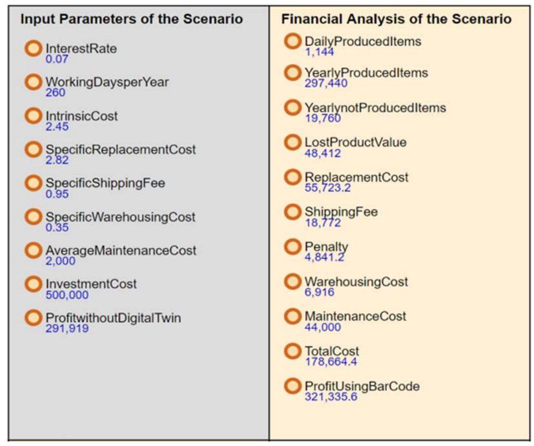


Fig. 9. Analysis of a conventional job-shop without digital twin deployment

The second scenario shows the impact of a digital twin deployment using barcode technology for identification and tracking of products in the job-shop manufacturing system on financial indicators. In this case the inaccuracy of the manufacturing system can be decreased using barcode technology: r_{INA}=1.20 % and f=2.20 %. The input parameters, the manufacturing- and logistics-related parameters, the total cost and the profit, as part of the simulation model are shown in Fig. 10, *a*.

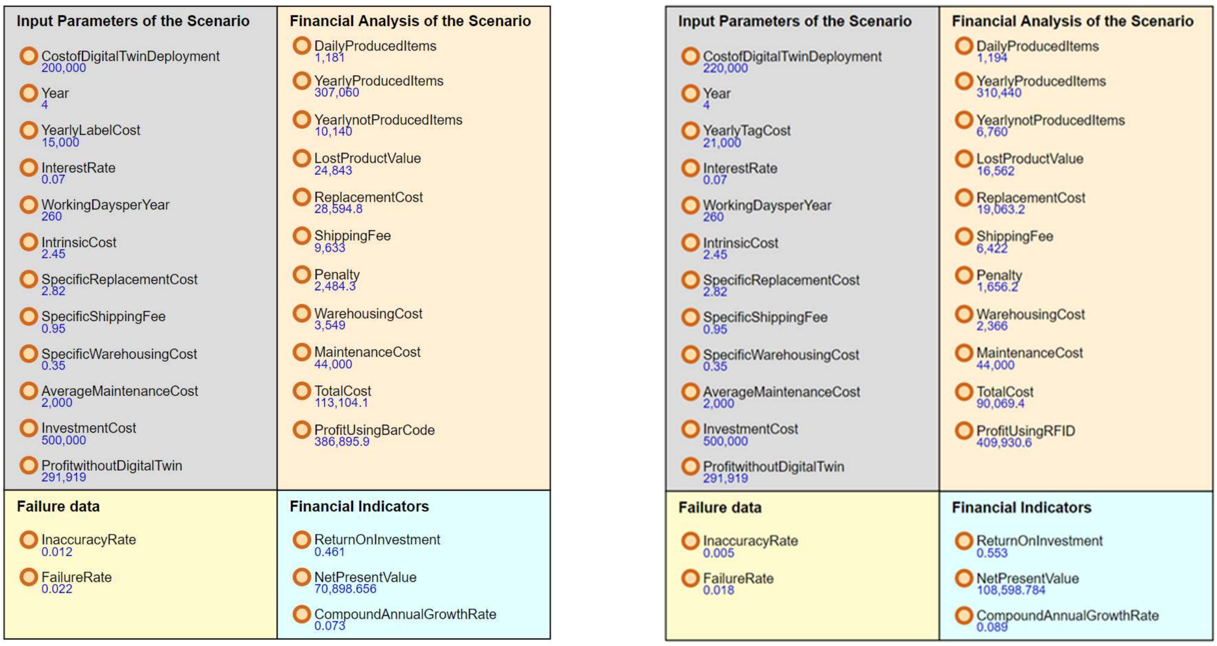
In the case of scenario 2, the cost of the digital twin deployment is 200000 EUR, the time frame is 4 years, the yearly label cost for barcode identification and tracking is 15000 EUR, and the rate of interest is 7 %. Based on this deployment and operation costs of the digital twin solution with barcode identification and tracking we can use the above described investment indicators as follows.

In the case of the computation of digital twin deployment's ROI the initial value is represented by the total extra profit of the job-shop manufacturing system resulted by the digital twin deployment. The cost of the investment includes the cost of the deployment and the yearly operation cost. In the case of the analyses of barcode and RFID solution this yearly operation cost includes the yearly tag or label cost.

In the case of the computation of digital twin deployment's NPV, the net cash inflow is represented by the extra profit resulted by the digital twin solution, the net cash output is the yearly tag or label cost, while the digital twin deployment cost can be taken into consideration as the investment cost.

For the solution of this equation, let's use the Excel *IRR* function, which returns the internal rate of return for a series of cash flows represented by the numbers in values. In this scenario *IRR*=22 %. *NPV*, *CAGR* and *ROI* are computed by Anylogic using the Java script. These computed financial indicators are shown in Fig. 10, *a*.

The third scenario shows the impact of a digital twin deployment using RFID technology for identification and tracking of products in the job-shop manufacturing system on financial indicators. In this case the inaccuracy of the manufacturing system can be significantly decreased using RFID technology. In this case the inaccuracy of the manufacturing system is 0.50 %, while the failure in the manufacturing system is about 1.80 %. The input parameters, the manufacturing- and logistics-related parameters, the total cost and the profit can be also computed as shown in the case of barcode application. In this case, the following values were computed as financial indicators: *ROI*=55.3 %, *NPV*=108598 EUR and *CAGR*=8.9 %.



a *b*

Fig. 10. Analysis of digital twin supported job-shop: *a* — with barcode-based identification and tracking; *b* — with RFID-based identification and tracking

The cost of the digital twin deployment is 220000 EUR, the time frame is 4 years, the yearly label cost for barcode identification and tracking is 21000 EUR, and the rate of interest is 7 %.

The input parameters, the manufacturing- and logistics-related parameters, the total cost and the profit, as part of the simulation model are shown in Fig. 10, *b*.

As the above-described analysis of the three scenarios shows, the digital twin solutions can significantly increase the cost-efficiency of job-shop manufacturing systems. This cost efficiency is influenced by the components of the digital twin solution. In this scenario analysis, let's focus on the application of barcode and RFID technologies of identification and tracking tasks of products to be produced in the job-shop manufacturing system.

As the comparison of the financial indicators show, RFID supported digital twin technology can lead to a more cost-efficient solution (Table 2).

Let's analyze the impact of the investment on the financial indicators, as shown in Fig. 11.

As the results of the analysis shows, the CAGR is constant, while ROI, IRR and NPV are decreasing. It is possible to conclude, that the zero value of the financial operators are at different deployment cost, which means, that the financial evaluation of digital twin deployments must be performed using more financial indicators.

The analysis of the impact of yearly tag or label cost on the financial indicators shows the same results. CAGR and NPV are constant, while the value of ROI and IRR is decreasing, as shown in Fig. 12.

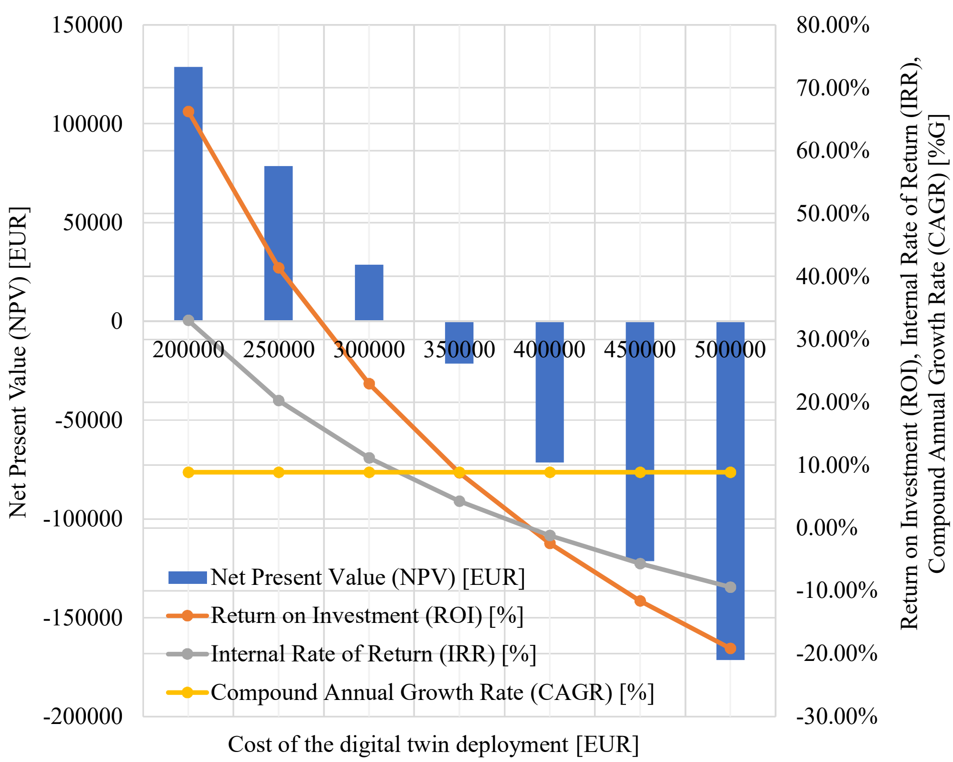


Fig. 11. Impact of digital twin deployment cost on the financial indicators

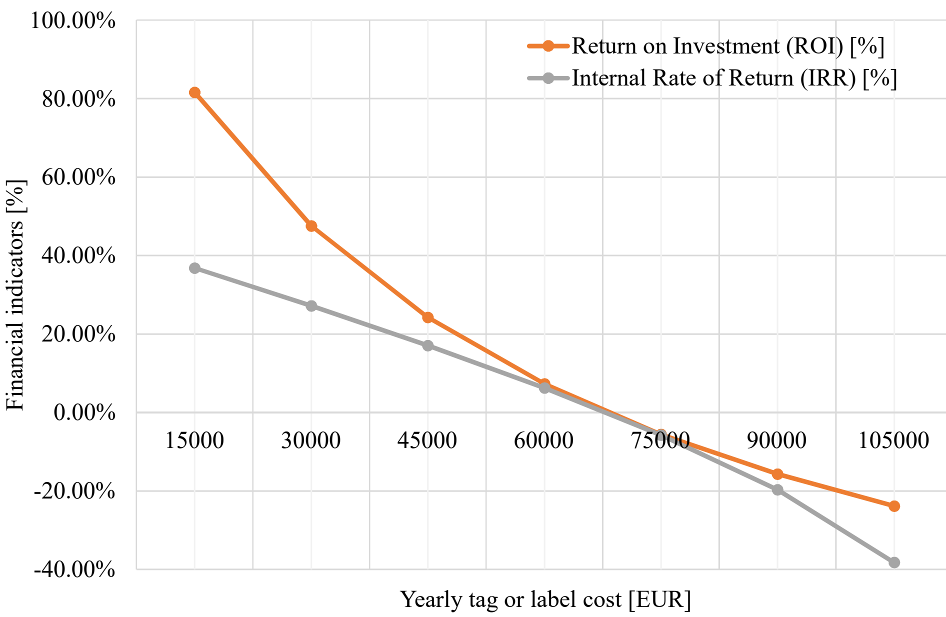


Fig. 12. Impact of yearly tag or label cost on the financial indicators

Table 2

Comparison of the main financial indicators of the scenarios

Financial indicator	Digital twin with barcode	Digital twin with RFID
ROI	46.1 %	55.3 %
NPV	70899 EUR	108598 EUR
CAGR	7.3 %	8.9 %

As a summary of the numerical results it is possible to conclude, that the proposed simulation-based approach is suitable for the financial evaluation of a digital twin deployment. This methodology is flexible, so it is possible to analyze not only the impact of identification technologies, but also other hardware and software on the economic aspects.

6. Discussion of results determining the impact of digital twin technologies on the performance of job-shop production

To improve the efficiency of the application of Industry 4.0 technologies, it is necessary to analyze not only the technological consequences but also to measure their financial impact. Determination of the short time and long-term financial impacts makes it possible to build, apply and operate a much more economical manufacturing system.

To determine the impact of different digital twin solutions on the performance and cost-efficiency of the job-shop production system, an integrated approach was proposed. The authors described a new approach, which is suitable to analyze the impact of digital twin deployment on the cost efficiency of job-shop manufacturing systems. The approach includes the following main phases:

1) analysis of the digital twin components to define the most important cost factors;

2) identification of the impact of digital twin on the performance indicators of the job-shop manufacturing system;

3) identification of the most important investment indicators to analyze the impact of different digital twins on the costs and profit;

4) agent-based simulation of the job-shop manufacturing system to measure the impact of different IoT technologies (in our cases different identification technologies including barcodes and RFID) on the performance;

5) scenario analysis to compare the potential digital twin deployment.

The results of the agent-based simulation showed that it is not enough to analyze the impact of digital twin solutions on the performance but their financial impact must be studied. As Fig. 9, 10 showed, the RFID identification technology-based digital twin solution can lead to a higher productivity. Their financial indicators are also significantly better, than in the case of barcode technology based digital twin solutions. The return on investment was 9.2 % higher for RFID-based digital twin, than for the barcode-based solution. The net present value was 53 % higher for RFID and the compound annual growth rate was 1.6 % higher for RFID than for barcode technologies (Table 2). This analysis showed, that RFID-based identification technologies have more significant impact on both performance and return on investment.

It is important to note that the operation of the physical system is not only determined by the digital twin, but that the human resources, the local control and the digital twin together influence the operation of the real-world system.

The managerial impacts of this research are the followings:

– the simulation-based analysis can support managerial decisions regarding the deployment of digital twin solutions;

– the analysis of the suitable IoT solutions (in this case the integration of barcode or RFID into digital twin) makes it possible to support the decision of choosing the suitable and most cost-efficient technologies;

– the analysis of the impact of digital twin on the technological and logistics performance of job-shop manufacturing system can lead to the reengineering of the technological and logistics processes to increase efficiency.

The advantage of this study in comparison with [2, 6–11] is that the proposed evaluation methodology makes it possible to analyzed not only the technological, but also the financial impact of the digital twin technologies on the manufacturing plant. In comparison with the works [33, 34], the simulation is suitable to solve not only technological and logistics problems, but also financial aspects of technological improvement can be analyzed.

The limitation of this study is that it does not take all components of digital twin solutions into consideration.

The disadvantage of this study is that the methodology was tested only in the case of job shop manufacturing.

These limitations and disadvantages define the potential future research directions: it is possible to extend our methodology and to analyze other manufacturing systems, for example the flow shop manufacturing or U-shaped manufacturing systems. It is also advisable to extend our methodology to be able to analyze more complex digital twin solutions.

7. Conclusions

1. Digital twin solutions can greatly enhance the productivity of manufacturing systems. The efficiency of digital twin solutions is greatly influenced by the technologies used. In this research, the most important physical and digital resources of the digital twin supported job-shop manufacturing were identified. These technologies are the followings: simulation, cloud computing, optimization, artificial intelligence, blockchain, smart sensors, big data, virtual and augmented reality, radiofrequency-based and barcode-based identification and tracking.

2. The identification of the most important performance indicators to measure the impact if digital twin solution on the performance of the job-shop manufacturing is carried out to make it possible to analyze the impact of different digital twin solutions on the performance of job shop production. These performance indicators are the followings: number of produced items, number of working hours, error rate or inaccuracy, failure in the production system, number of not produced items: this performance indicator can be used to measure the fulfillment rate of customers' demands, utilization of manufacturing, material handling and human resources, inventory level and inventory cost, manufacturing cost and materials handling cost.

3. For the technologies presented in this research work, cost factors can be identified to estimate the investment and operational costs of a digital twin solution. The used financial indicators to analyze the impact of digital twin solutions are the followings: Return on Investment, Net Present Value, Internal Rate of Return and Compound Annual Growth Rate.

4. An agent-based simulation model has been developed to evaluate the economic efficiency of a digital twin solution for different manufacturing systems. The developed model integrates the analysis of parameters related to the productivity of the manufacturing system to determine the economic indicators that can be derived from it.

5. The analyzes showed that the return on investment of digital twin solutions based on RFID identification technology is significantly higher than that of barcode identification technology in the scenario under study. It can be concluded from the research results that Industry 4.0 technologies make it possible to improve productivity, efficiency, flexibility, but the complexity, the used technological components can significantly increase the investment and operation costs, therefore it is important to analyze the suitable potential solutions from both technological and financial point of view. The numerical analysis of a job shop manufacturing scenario shows more significant financial impact (ROI, CAGR, NPV and IRR) for radiofrequency identification technology-based digital twin solution, than in the case of barcode technology. In the case of digital twin with RFID the ROI was 46.1 %, the NPV was 70899 EUR, and the CAGR was 7.3 % for a 4 years long time period. In the case of barcode identification and tracking, the ROI was 55.3 %, the NPV was 108598 EUR, and the CAGR was 8.9 %.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Data will be made available on reasonable request.

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