D6.2
Use case Implementation analysis

BBTWINS
Agri-Food Value Chain Digitalisation for Resource Efficiency

Circular Bio-based Europe Joint Undertaking

Bio-based Industries Consortium

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1. Introduction

1.1. Executive Summary

The BBTWINS project, funded under the Horizon 2020 Bio-based Industries Joint Undertaking (BBI JU), is an ambitious initiative aimed at transforming agri-food value chains through the deployment of advanced digital technologies. By integrating Digital Twins (DTs), blockchain-based traceability systems, and biomass valorization models, the project demonstrates how digitalization can address key challenges in food production, supply chain efficiency, and circular bioeconomy practices. This deliverable, D6.2 – Use Case Implementation Analysis, presents the outcomes of real-world testing and validation of the BBTWINS tools across two distinct agri-food processes and value chains targeted by the project: fresh fruit production, represented by the DIMITRA cooperative in Greece, and pork production, represented by the integrated operations of PORTESA, CARTESA, and AIRE SANO in Spain. The central goal of the BBTWINS project is to design, implement, and validate a modular platform that supports decision-making, resource optimization, and waste reduction across agri-food chains. To achieve this, the project developed two comprehensive DT frameworks simulating the end-to-end operations of fruit and meat production systems. These DTs capture everything from energy consumption and worker flows to product throughput and waste streams. In parallel, a blockchain-enabled traceability platform was introduced to reinforce supply chain transparency. Simulation models were developed to explore the feasibility of converting production residues into valuable bio-based products or renewable energy.

The DIMITRA cooperative comprises 170 producers of fresh fruits such as peaches, nectarines, cherries, apples, and apricots. The DT designed for DIMITRA replicates its internal operations, from sorting and packaging to the storage and dispatch of goods. The validation process focused on seven quantifiable parameters—total energy produced, total energy consumed, assembled pallets, filled wooden boxes, box stickers, fruit stickers, and waste generation. These parameters were selected due to their traceability capacity through official records, which allowed for a reliable comparison between real-world data and simulated outcomes. The DT demonstrated remarkable precision, with the majority of deviations well below the 20% error margin defined as acceptable within the project. For instance, the total energy production error was only 1.3%, and waste output deviated by just 1.1%. Moderate overestimations were found in consumables such as wooden boxes and fruit stickers, ranging between 10–15%, and the only parameter exceeding the margin was total energy consumption, which showed a 21.2% deviation. However, this discrepancy was justified by the limited data set used in the simulation, which accounted for only four fruit types out of the many produced by DIMITRA, resulting in reasonable generalizations about the remaining operations.

In contrast, the pork value chain led by PORTESA, in conjunction with its affiliated companies CARTESA and AIRE SANO, required a multi-tiered simulation approach due to the scale and complexity of its vertically integrated system. Separate DTs were developed for the fattening farm, feed mill, processing plant, and biomass systems. Each DT simulated specific operational elements, from feed logistics and slaughterhouse energy consumption to production output and distribution. Validation was primarily conducted at the CARTESA processing level, where real data on gas consumption, animal throughput, and total product weights were compared to DT projections. Again, the results supported the reliability of the model, with burner gas consumption deviating by just 0.17% and boiler gas use by 6.2%. The estimated number of pigs processed showed a 13.9% error, and total product weight had a 15.7% deviation—both within acceptable limits.

The only parameter exceeding the threshold was the quantity of distributed meat products, with a deviation of 22.4%, which was attributed to unpredictable variables in post-processing logistics not yet fully incorporated into the DT. These results underline the potential of DTs as reliable forecasting and planning tools in large-scale, multi-facility agri-food enterprises.

A major innovation introduced alongside the DTs was the blockchain-based traceability system, developed by Stelviotech. This platform was tested with both use cases and proved instrumental in enhancing supply chain transparency, data integrity, and user-controlled information sharing. For PORTESA and its affiliates, the system enabled full traceability from individual animals to the final meat product, offering unmatched granularity and reinforcing food safety protocols. Wholesale clients could access detailed shipment histories and quality information, while consumers could retrieve origin and production details by scanning QR codes. In the case of DIMITRA, the platform effectively tracked fruit movements from field to dispatch, although traceability was limited to the orchard level, rather than individual trees. This limitation reflects intrinsic sectoral characteristics rather than technological constraints, and it highlights the need for sector-specific customization when deploying such systems. Both companies acknowledged the value of the tool but emphasized the importance of investing in staff training and reducing the time burden associated with manual data entry during implementation.

BBTWINS also explored how DTs can support the valorization of biomass generated along the agri-food value chain. For PORTESA, a simulation was developed for a future biogas plant converting pig waste into energy. While no physical facility exists yet, the DT was benchmarked against experimental data from research partner CVR, validating the feasibility of biogas production under realistic scenarios. DIMITRA’s biomass model explored the potential for extracting high-value compounds such as pectin and polyphenols from fruit residues. While practical implementation remains limited, the simulations offer guidance for future infrastructure planning and underline the economic potential of valorizing agri-food by-products in line with circular economy principles.

A cornerstone of the BBTWINS validation methodology was the definition and application of Key Performance Indicators (KPIs). A hierarchical model was established to differentiate between direct measurements (e.g., production time, machine uptime), basic KPIs (e.g., availability, first-time quality), and comprehensive KPIs (e.g., overall equipment effectiveness). These indicators provided not only a validation mechanism for the DTs but also a framework for continuous performance monitoring and improvement. The selected KPIs were tailored to reflect the operational realities of both use cases and covered dimensions such as energy efficiency, production flow, traceability coverage, waste ratio, and worker efficiency. As such, the KPI framework became an integral component of the decision-support environment fostered by BBTWINS. The results presented in this deliverable underscore the robustness, accuracy, and adaptability of the digital tools developed under the BBTWINS project. The DTs demonstrated high fidelity to real-world data, confirming their potential to support forecasting, resource optimization, and scenario simulation. The traceability system introduced new levels of transparency and control, particularly in the meat sector, while the biomass valorization models illustrated the potential for future circularity and sustainability interventions.

At the same time, the analysis highlights that technological innovation alone is not sufficient. Full realization of the benefits offered by DTs and blockchain platforms requires complementary investments in human capacity, digital infrastructure, and change management strategies. Organizational readiness, user familiarity with digital systems, and long-term alignment with strategic goals are all critical enablers of digital transformation. Looking forward, the BBTWINS methodology offers a scalable and replicable blueprint for digital innovation in the bio-based economy. As the project progresses toward its final phase, attention should focus on upscaling successful models, refining platform usability, integrating advanced features such as predictive analytics, and supporting broader deployment across European agri-food value chains. Through continued collaboration among industry, technology developers, and research institutions, BBTWINS has laid a solid foundation for future-oriented, data-driven agrifood systems that are more transparent, resilient, and sustainable.

1.1.1. KEY SERVICES AND CONTRIBUTIONS

- **DIMITRA**
    - Providing useful information about the internal way of operation
    - Identifying strengths and weaknesses in their value chain
    - Identifying which fields of the value chain can be improved.
- **PORTESA**
    - Providing useful information about the internal way of operation
    - Identifying strengths and weaknesses in their value chain
    - Identifying which fields of the value chain can be improved.
- **CluBE**
    - Proposing actionable improvements in the value chain
    - Developing a methodology for the current evaluation of the situation
    - Developing KPIs to measure the improvement of the value chain

1.2. Purpose and Scope

Define and use the methods and tools by which the use cases are tracked. The use cases will be monitored and assessed in a way that is sufficiently open, concise, and clear as to how the agreed targets and indicators are measured and quantified. This should be done in a way that is transparent and objective. Moreover, a comprehensive monitoring data collection approach was developed by designing a unified framework for harmonized data collection, analysis, and storage. In addition to monitoring the use cases' progress, contextual information had to be collected as well (i.e. developments that are not intentionally related to the policy intervention, although they may be influenced by it, such as economic growth, break-through technologies, new behavioral patterns etc.).

1.3. Methodology

To produce this deliverable and the effective validation of the digital tools a structured methodology plan was developed. The steps required for understanding the tools needed a successful analysis for both DIMITRA and POERTESA are presented below :

1. ***Literature review of KPIs on food value chains****: Understanding the need for such measurement methods in the food industry both for validation and optimization purposes.*
2. ***Literature review of KPIs definition methodology****: The theory which supports the development of KPIs specified for the food sector.*
3. ***Creating the hierarchy of KPIs on which the whole methodology will be based****: Creating the KPIs based on which the whole validation and optimization will be performed. The KPIs will be developed based on the hierarchical model described in the literature reviews.*
4. ***Validation of the digital tools for PORTESA and DIMITRA****: Testing of the digital tools developed for both companies and comparison with real data to complete the validation method.*
5. ***Optimization model:*** *By utilizing the digital tools along with the input from DIMITRA minor adjustments were made to study the impact on the value chain.*

1.4. Structure of this document

This document is structured to provide a comprehensive overview of the implementation, validation, and analysis of the digital tools developed within the BBTWINS project. It begins with an introduction outlining the project's objectives, scope, and methodological approach. This is followed by a detailed description of the two primary use cases—DIMITRA and PORTESA—alongside the key technological components applied: Digital Twins, blockchain-based traceability systems, and biomass valorization simulations. Subsequent sections present the definition of Key Performance Indicators (KPIs) and the hierarchical model used to assess performance. The validation process is then described in depth, comparing simulated outputs with real-world data to evaluate the accuracy and reliability of each tool. The document continues with an analysis of results, discussing key findings and implications, before concluding with a reflection on the overall impact, challenges, and future potential of the BBTWINS solutions. Supporting figures, tables, and annexes are included throughout to substantiate the findings and enhance clarity.

1.5. Relationships with other deliverables

D6.2 uses input from the work done in WP 1-5. D6.2, monitors and validates the agri-food processes and value chains (use cases of Tasks 6.1 and 6.2) by implementing and quantifying specific targets and indicators. In close collaboration with Task 1.2, Task 1.3 and Task 3.1, D6.2 prepares the testing protocols/processes set up and configures the Digital Twins as specified by WP5, as well as the monitoring software/hardware tools and the day-to-day work details for performing the use case testing scenarios on the use case testing sites (Spain and Greece). The technologies selected in Task 2.4 which is correlated with D2.5 were used for production of this deliverable. More specifically, D2.5 defines what to simulate, and D6.2 shows how those simulations perform when digitally implemented and validated against real-world operations.

2. Use Case Description

2.1. Brief Introduction of the use cases

Portesa is a livestock company. Its main activity is pork livestock breeding for the meat (pork) value chain, at farms located in the province of Teruel. The farms and the production process conform to the highest standards, with an optimum level of animal welfare. For the optimal feeding of its livestock, Portesa operates a feed factory and engages in an integrated production process, managing the genetics and choosing the best cereals to feed their livestock (pigs), placing a high value on the traceability of every step, and maintaining precise food security controls. There are three important phases within Portesa's manufacturing process. Piglet production up to 6 kilogram, weaning piglets from 6 to 18 kg, and fattening pigs from 18 to 125 kg. Additionally, Portesa provides Carnes de Teruel (Cartesa), the meat industry plant, with all of its production. Cartesa's activities comprise slaughtering, cutting and producing different formats of fresh pork meat, as well as salted and cured products. Finally, Cartesa provides the shoulders and hams to a third company, Aire Sano. Portesa, along with Cartesa and Aire Sano, form part of an integrated production process, which also conforms to a traceability process that is a benchmark throughout Europe. Furthermore, Portesa, Cartesa and Aire Sano are strongly committed to research and innovation to utilize sustainability and residue recovery models to implement effective circular economy practices.

Dimitra is a cooperative that focuses on the production, management, and distribution of fresh fruits, such as peaches, nectarines, apples, cherries, and apricots. The cooperative consists of 170 producers of fresh fruits. The producers own the fields on which they cultivate and harvest the produce. Sorting, packaging, and storage of fruits is being carried out in a modern co-owned facility with controlled atmosphere cold stores, various mechanical equipment and advanced technology equipment on the sorting and packaging line. Dimitra also distributes approximately 50% of its fresh fruits, especially peaches and nectarines, in foreign markets.

2.1.1. PROCESS AND LOGISTICS OPTIMIZATION THROUGH DIGITIZATION AND ENABLING TECHNOLOGIES

This use case will analyze and simulate the animal food production and dispatch process (PORTESA) and the fruit ordering process, including production forecasting.

In the case of the meat sector, the use case will evaluate the Animal Food Supply process, which is representative of the value chain from the feed mill to the farmers. Furthermore, to complete the process and logistics optimization, we have to make a digital counterpart of the meat value chain, which involves the activities carried out in the slaughtering house, the salting, and the curing facilities, so that the DT can be used to generate reliable production forecasts in terms of worker's needs, production losses and demand coverage. This DT implementation will simulate the meat products ordering process and will cover the value chain from the farm to the slaughterhouse and finally, to end users.

In the case of fruit sector, The DT will have to simulate the fruit ordering process, which involves all the actors in the fruit value chain. The use case will then be validated in order to use the finding for production forecasting on crops and factory. The use case is designed to identify opportunities for improving the efficiency of the entire value chain, ensuring the biomass supply, and reducing waste that occurs due to quality defects, conflicting incentives, overproduction, or sub-optimal scheduling of logistics and production. To accomplish this, the data produced by the simulations carried out through the DT, will be compared with data from real environment operations and contrasted with logistics and production plans produced by advanced optimization tools that consider the quality properties of the feedstock and operations through the entire value chain.

2.1.2. TRACEABILITY AND TRANSPARENCY ASSISTED BY BLOCKCHAINS

An integrated traceability system based on blockchain is among the primary incentives towards using enabling technologies for Portesa. Such a system will inform the consumer about the origin and traceability of Portesa's products in all the stages of the production process and consequently increase and improve the food safety. This use case will test and validate the traceability system implemented in WP4 as is integrated and used by the DT, from the perspective of wholesale/retail clients, as well as from an individual consumer's endpoint (Information exchange will based on blockchain technology provided by Stelviotech which will also provide security and robustness to the data involved). In this scenario a wholesale/retail customer will be able to request logistical data containing costs, dates, quality parameters etc. These data will be linked to order numbers, shipment numbers, etc., any parameter in general that is traceable in any stage of the value chain on a B2B level. On the other hand, a consumer will access information related to food quality, location, and production details, by scanning with a smartphone a certain area on the product's package (most likely a qr-code printed on the package). Both roles are defined and analyzed in D4.1.

Blockchain traceability from the perspective of wholesale/retail clients, as well as from an individual consumer's endpoint (Information exchange will be based on blockchain technology provided by Stelviotech which will also provide security and robustness to the data involved). In this scenario a wholesale/retail customer will be able to request logistical data containing costs, dates, quality parameters etc. These data will be linked to order numbers, shipment numbers, etc., any parameter in general that is traceable in any stage of the value chain on a B2B level. On the other hand, a consumer will access information related to food quality, location, and production details, by scanning with a smartphone a certain area on the product's package (most likely a qr-code printed on the package). Both roles are defined and analyzed in D4.1.

2.1.3. BIOMASS PROCESSING

The farms produce two broad categories of biomass residues: i) Pig carcasses, that are currently incinerated; ii) Pig fluid manure that is used as an organic fertilizer. In the slaughterhouse, residual biomass is destinated to produce protein flour and fat of animal origin to use in animal feed or biofuels. Furthermore, the sludge from the treatment plant is used as fertilized and blood as raw material for the amino acids of special fertilizers. In the dryer's factories, residual biomass products are destinated to produce protein flour for animal feed mainly. Therefore, WP6 needs a use case that will drive the optimization of the feedstock value chain in terms of availability, quality, resource efficiency, and economic profit, as well as an opportunity to test other valorization alternatives. The use case will create the digital counterpart of biomass processing. Findings and data produced by the simulation will be used for waste valorization analysis in order to create value from the different types of waste produced at Portesa's facilities such as pork bones, fat, skin, or hair. Furthermore, the use case will also explore the potential and sustainability of a biogas plant, to cover part of the energy needs of Portesa's facilities. Furthermore, the use case will also analyze the viability of mixed energy production solutions, by combining biogas alternative renewable sources such as photovoltaics. Those deemed as feasible in terms of cost and location will be included in the DT, to study what-if scenarios of energy production by renewable energy sources.

Dimitra residual biomass is currently treated as follows: i) during pruning, the biomass is left at the field, and it is used as green manuring; ii) during the sorting process, all fruits that are not selected for sale are transferred at non-competitive price to a juice production company. Although research has been developed on the analysis of the main elements of peaches and its possible uses in pharmaceutical or cosmetic companies, there are inadequate data to consider this approach as a viable waste management process. Nevertheless, the Cooperative (Dimitra), seeks for alternative uses of fruit waste, through the extraction of high-added value compounds such as pectin, glycosylates, proteins and phenolic and polyphenolic compounds, suitable for functional foods and nutraceutical products. This DT of biomass processing within the Cooperative aims to investigate waste valorization options and the potential to create value from the different types of waste, such as seeds, fruit skin or hair from peaches. The biogas potential will also be considered although Dimitra produces plant (fruit) biomass which contributed approximately 25% of the raw materials used for biogas production. However, the possibility to use alternative renewable energy sources is more likely. Therefore, the use of photovoltaics is to be included in this use case.

3. KPIs Definition

Key performance indicators (KPIs) are quantifiable measurements used to gauge a company's overall long-term performance. KPIs specifically help determine a company's strategic, financial, and operational achievements. KPIs vary between companies and between industries, depending on performance criteria. For example, a software company striving to attain the fastest growth in its industry may consider year-over-year (YOY) revenue growth as its chief performance indicator. Conversely, a retail chain might place more value on same-store sales as the best KPI metric for gauging growth.

At the heart of KPIs lie data collection, storage, cleaning, and synthesizing. The information may be financial or non-financial and may relate to any department across the company. The goal of KPIs is to communicate results succinctly to allow management to make more informed strategic decisions.

3.1. Food process companies (fpc) and digital twins_kpis measurement

The KPIs measures mainly depend on the availability and quality of data at the strategic level, whereas the effectiveness of the production process at the operational level. Although, both practices are essential for DT implementations and execution processes. In FPC, the ultimate purpose of the DT is to mimic the behavior of the operational and strategic optimizations with the incorporation of a man-machine system (Kang et al., 2016). We have provided a broader framework of KPIs in Figure 1. The term KPIs is frequently used to measure the system's performance comprehensibly based on time, quality, and cost. Early KPIs systems are primarily considered for financial aspects, but the production standards such as VDMA 66412-1, ISO 22400-1, ISO 22400-2, and their subsets provide more than 100 KPIs to measure the relevant performance ((Chae, 2009)). However, (Soltanali et al., 2021) proposed FPC production performance indicators and specified numerous performance tools such as Kaizen, Kanban, Poka Yoke, Shojinka, and 5S ((Braglia et al., 2020)). Figure 1 presents various KPIs based on the findings of (Kang et al., 2016) and (Stricker et al., 2017). (Kang et al., 2016) referred to the report of ISO 22400–1 and ISO 22400–2. They stated that production KPIs reflect the industry's critical success factors in quantifiable and strategic measurements to ensure continuous improvement of production systems. Therefore, we have developed this paper to focus on the production KPIs and evaluate the traditional approach with the DT-based approach.

3.2. The Hierarchical model

In production systems, many raw measurement elements are monitored and collected, such as, machine's busy time and production volume. Based on these elements, KPIs of interests to engineers and managers can be derived and evaluated, for instance, efficiency or quality. Thus, the directly monitored elements become the supporting metrics for KPIs. These KPIs mostly reveal a single aspect of system performance only, thus are categorized as basic KPIs. To represent the overall performance, more comprehensive KPIs, supported by several basic KPIs, can be obtained. For example, the overall equipment effectiveness (OEE) index, which is based on individual equipment's (or a group of equipment' overall) working and failure time allocation, provides information related to production efficiency and production loss. The throughput of a production line is dependent on all the machines, the buffers, their positions and interactions. Therefore, based on these attributes, the supporting role, single function, and comprehensive feature of these elements or indicators, we introduce a hierarchical structure to categorize KPIs and the supporting elements. Specifically, such a structure consists of three categorized levels: direct measurement or supporting elements, basic KPIs, and comprehensive KPIs, as shown in Figure 1.

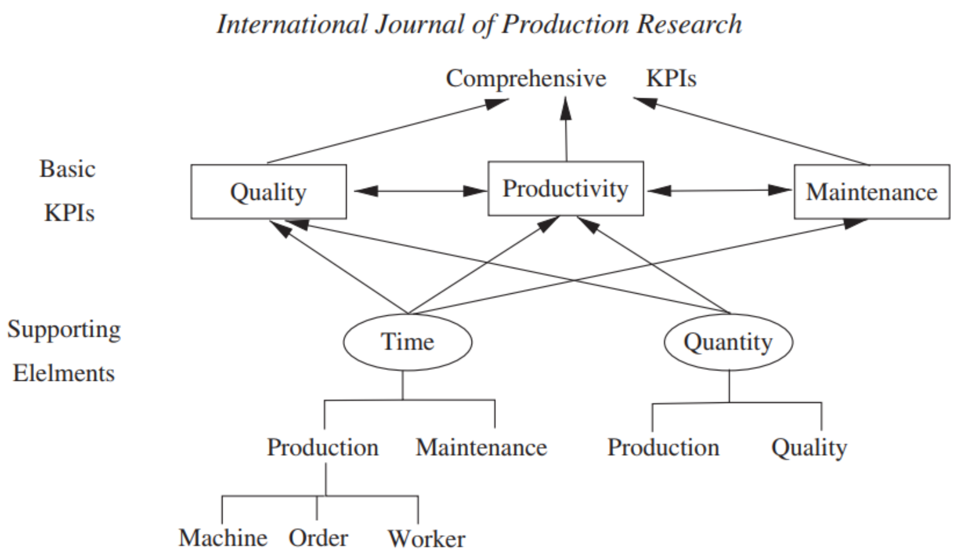

Figure 1: KPI categorization

In addition, we group the parameters based on their functions or attributes in each level. In the supporting elements level, the measurements can be divided into time and quantity groups. Within time group, there will be time measurements related to production and maintenance, from the point of view of machines, production orders, and operating workers. In quantity group, measurements are related to quantities on both production and quality. For basic KPIs, the attributes are related to production, quality, and maintenance. These KPIs are calculated by the direct measurements.

They all contribute to the comprehensive KPIs. Note that, the relationships not only exist between different levels of KPIs and supporting elements, but also can link KPIs within the same level, which are shown as double arrows between quality, productivity, and maintenance.
Such a hierarchical framework explicitly indicates the causal relationships between different levels of KPIs and supporting elements. Clearly, such a categorization is not unique. Other types of grouping structure can be developed based on specific goals. Below, the KPIs and supporting metrics illustrated in Figure 1 are described. Since supporting elements are needed to derive basic and comprehensive KPIs, these elements are presented first.

The supporting elements are the data directly monitored and collected during production. Using these elements, the basic KPIs can be derived. In the proposed framework, the supporting elements can be divided into two categories: time and quantity. Some examples of supporting elements and their categorization are presented below in Figure 2.

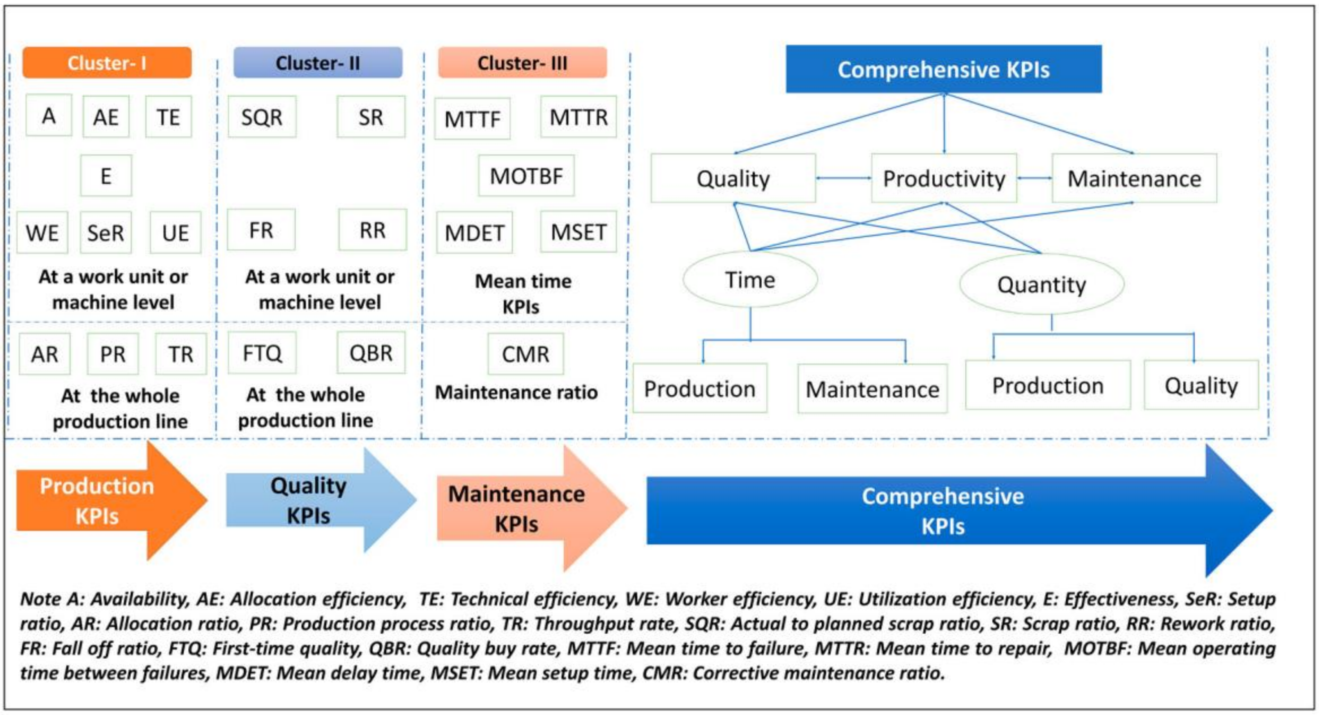

Figure 2: KPIs examples

4. Validation Process

The adoption of digital twin technologies in the agri-food sector marks a pivotal evolution toward integrated, data-driven operations. Yet, the true measure of their impact lies not in conceptual promise, but in demonstrable, real-world performance. This is where rigorous validation becomes indispensable. Validation serves as the critical bridge between model design and operational reliability, ensuring that each digital twin accurately mirrors its corresponding physical system and aligns with the practical requirements of end users. In complex and regulation-sensitive domains such as fruit and meat production, validation is not merely a technical step—it is a foundation for trust, traceability, efficiency, and compliance. Furthermore, it enables improvements with the iterative system, fosters user confidence, and enhances decision-making processes based on real-time, reliable insights. This chapter presents the validation framework employed across three distinct use cases, offering grounded lessons from field implementation and pinpointing key opportunities for refinement and future scalability.

4.1. Validation of process and logistics optimization

As outlined in Chapter 2.1.1, the process and logistics optimization use case is centered on simulating and enhancing production and logistics workflows within two key agri-food sectors: meat and fruit. In the meat sector, the digital twin (DT) models the full value chain—from animal feed supply through slaughtering, salting, and curing—enabling detailed production forecasting, including workforce requirements, potential losses, and demand fulfillment. In the fruit sector, the DT simulates the entire ordering and production pipeline, aiming to improve forecast accuracy, increase operational efficiency, and minimize waste.

The validation approach for both sectors involve comparing the outputs generated by the digital twin with actual operational data collected from the two partner companies, DIMITRA and PORTESA. The digital twin mirrors each company's internal value chain, simulating worker movements, shifts, and the dynamics of equipment usage. By integrating this operational data with static and variable input parameters—such as equipment characteristics, utility costs, and product pricing—the DT calculates a range of performance indicators, including energy production and consumption, consumable requirements, costs, and estimated waste.

The digital twin developed for DIMITRA, illustrated in Figure 3, provides a detailed virtual replica of the cooperative's headquarters, including internal routes followed by employees throughout the production cycle. The left column of the figure displays the input parameters—configurable values that reflect the cooperative's operational decisions—while the right column displays the calculated outputs, derived through pre-defined formulas based on those inputs. These DT-generated outputs form the basis for the validation process, wherein they are systematically compared against real-world data provided by the companies.

Given the complexity and variability inherent in large-scale agri-food operations, a tolerance threshold was introduced: deviations of up to 20% between the digital twin and real-world data are considered acceptable.

Additionally, the validation was constrained to measurable outputs for which official records exist, as not all DT-calculated parameters were available or tracked by the companies.

Figure 3: DIMITRA Digital Twin

The comparison between the digital twin outputs and the real-world data reveals a deviation of less than 20%, confirming that the digital twin delivers results closely aligned with actual operations. This level of accuracy demonstrates the reliability of the model in simulating real-life conditions. The specific values used in the comparison are presented in Table 1. It is important to note that not all parameters exhibit the same level of deviation, which is expected. As previously discussed, the digital twin calculations are based on a set of predefined formulas, while real-world operations are often influenced by unpredictable factors and operational variances that cannot always be fully captured by the model. Nonetheless, the observed deviations remain within an acceptable margin, supporting the validity of the digital twin.

Table 1: Comparison of values produced by the DT with real data of DIMITRA.

Parameters	Data produced from DT	Real Data	Error
ENERGY.TOTAL_Produced (kWh)	258.481,3	255.000,00	1,3%
ENERGY.TOTAL_consumption (kWh)	200.323	165.301,93	21,2%
MATERIAL.Assembled_pallets	559	620,00	9,8%
MATERIAL.Filled_wooden_boxes	88094	77200,00	14,1%
MATERIAL.Box_stickers	88094	77000,00	14,4%
MATERIAL.Fruit_stickers	1938111	1700000,00	11,76%
WASTE.Quantity	34377,8	34000,00	1,1%

In the case of DIMITRA, seven key parameters were analyzed, focusing on energy, consumables (materials), and waste. These specific categories were selected because they are both quantifiable and supported by recorded operational data, ensuring the reliability of the evaluation and minimizing the influence of external variables. This approach allows for a more precise validation of the digital tool's performance.

The results demonstrate that the digital twin (DT) provides a high level of accuracy, with most parameters showing a percentage error below the 20% threshold. The best-performing metric is the total energy produced, with the DT estimating 258,481.3 kWh compared to the actual 255,000 kWh, yielding an impressively low deviation of just 1.3%. Similarly, the estimation for waste quantity is remarkably accurate, with only a 1.1% deviation (34,377.8 kg vs. 34,000 kg). In terms of materials, the DT slightly overestimates across all subcategories, with deviations ranging from 9.8% to 14.4%. For example, it predicts 559 assembled pallets compared to the actual 620 (9.8% error), and 88,094 filled wooden boxes against a real figure of 77,200 (14.1% error). Similar patterns are observed in the estimation of box stickers and fruit stickers, which show errors of 14.4% and 11.76%, respectively.

The most significant deviation occurs in the energy consumption parameter, where the DT estimates 200,323 kWh versus the actual 165,301.93 kWh, resulting in a 21.2% error—just above the predefined acceptability threshold. However, this discrepancy is still considered reasonable given the current limitations of the digital twin. Notably, the model does not yet account for the full spectrum of DIMITRA's operations, which involve multiple fruit types and varieties. The project simulation includes only four fruits, requiring the DT to make generalized assumptions for the remainder of the production. These simplifications naturally contribute to a higher margin of error in complex, variable-dependent metrics such as energy consumption.

The same validation approach was applied to the PORTESA case. However, given the larger scale of the company and its integration with other entities within the same group—such as Cartesa and Aire Sano—separate digital twins were developed to represent each segment of the value chain. Beginning from the start of the process, Figure 4 represents the fattening farm calculating the potential by products and the weight statistics of the pigs. Since these values have occurred by multiplying the number of pigs with the quantity of products produced, the validation on this digital twin can be excluded due to the simplicity of the tool and the factors. The next step is the feed mill (Figure 5) which in this case simulates the distance covered by the drivers between the facilities. The purpose of this digital tool is to find the optimized route in collaboration with VTT. Even though the model produces a route which is supposed to be optimized by decreasing the driven distance and time, it can only be validated if it is applied in the reality. Since this hasn't happened and there are also many external factors which affect this route it is to be validated when and if implemented.

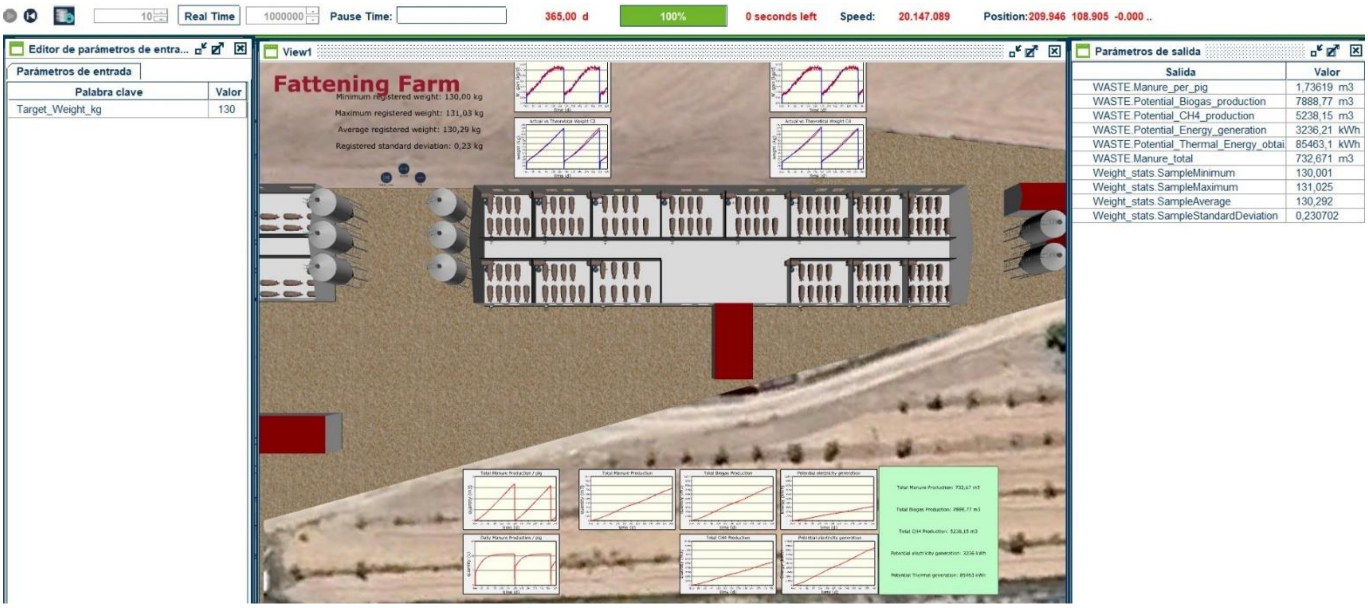

Figure 4: Digital Twin of the Fattening farm

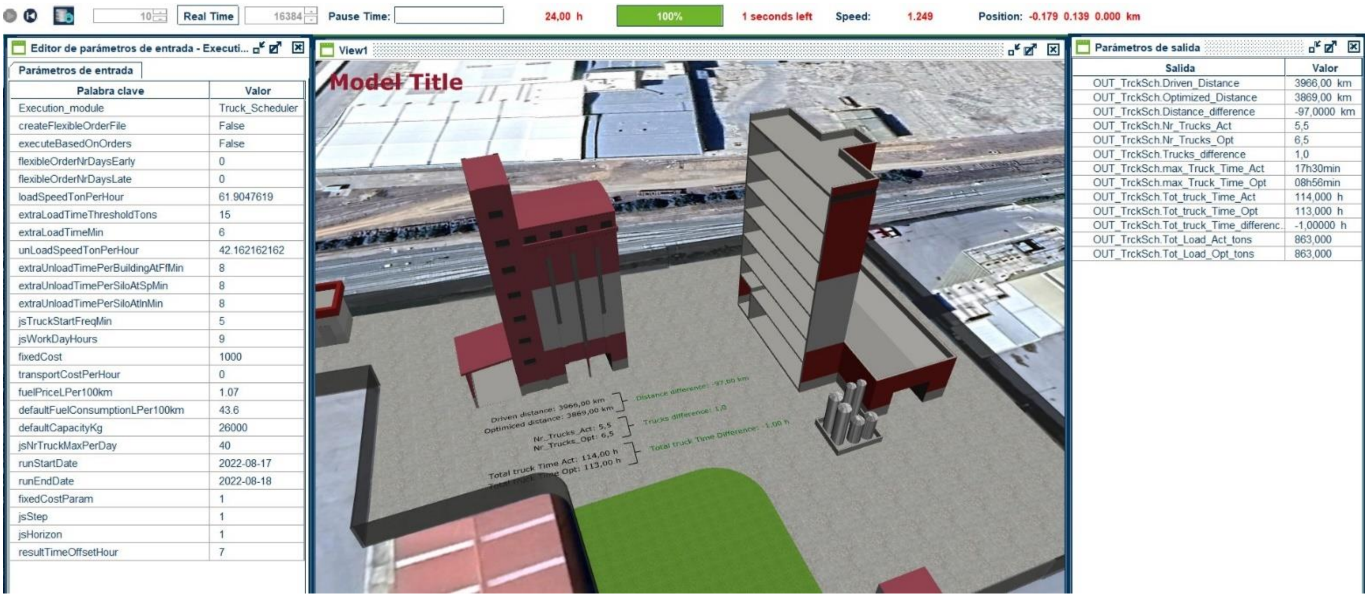

Figure 5: Digital twin of the Feed Mill

Moving on to the next station of the process, the facilities of Cartesa as shown in Figure 6, contain many data which can be compared with real ones since there are the necessary documents to support them. The validation process of the data that occurred from the Cartesa DT is similar with DIMITRA. Data such as energy consumption, production Kg and Waste can be backed and verified with dedicated documents. This consistency enhances the relevance of the comparison, as it allows for an assessment not only of the digital twin's accuracy but also of how data volume and company size may influence the tool's performance. The parameters evaluated for the PORTESA, Cartesa, and Aire Sano digital twins are summarized in Table 2.

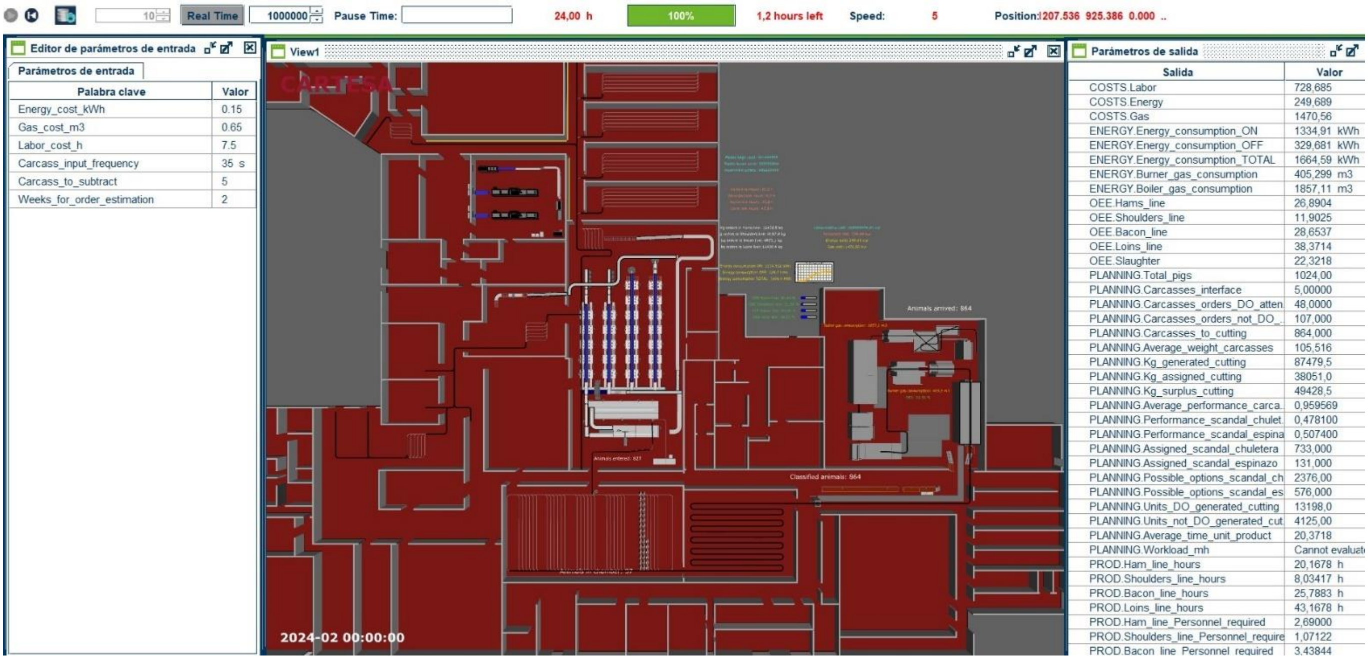

Figure 6: Digital Twin of the Facilities of CARTESA

Similarly to the DIMITRA use case, the Digital Twin developed for CARTESA demonstrates a high level of accuracy, with most of the evaluated parameters falling below the 20% error threshold. This confirms the tool's potential as a reliable decision-support system, especially in terms of operational planning and energy management.

Notably, the energy-related parameters show particularly strong performance. The total energy consumption—calculated as the sum of burner and boiler gas consumption—closely aligns with the real data. The burner gas consumption exhibits an exceptionally low deviation of just 0.17% (405.29 vs. 406 units), while the boiler gas consumption shows a modest error of 6.2% (1,857 vs. 1,748 units), indicating that the digital twin effectively replicates the plant's energy use with minimal deviation. Regarding production and planning, the results remain within an acceptable range, though they show slightly higher variance. The total energy consumption for the duration the digital twin represents is 801.7 kWh while the real energy consumption is 893 kWh. This difference shows a 10.2% difference which is within that acceptable range. The number of pigs processed (planning) is estimated at 1,024 compared to the actual 899, resulting in a 13.9% deviation. Similarly, the total production in kilograms is predicted at 87,531 kg versus a real value of 103,800 kg, corresponding to a 15.7% error. These figures, while not as precise as the energy metrics, are still within acceptable margins and reflect the digital twin's capability to model production processes effectively.

The only parameter that exceeds the 20% error threshold is the distributed kilograms of product, which shows a deviation of 22.4% (38,158 kg estimated vs. 49,173 kg actual). This discrepancy may be attributed to limitations in the available data regarding post-processing logistics and distribution schedules, which are often subject to greater variability and external influences not fully captured in the digital twin's current configuration. Overall, the CARTESA and DIMITRA digital twin proves to be a robust and reliable tool for simulating energy usage and supporting operational planning. With minor refinement, especially in the modelling of distribution processes, it has the potential to further enhance decision-making accuracy and efficiency across the production chain.

Table 2: Comparison of values produced by the DT with real data of PORTESA, CARTESA and Aire Sano

Parameters	Data produced from DT	Real Data	Error
ENERGY.Energy_consumption_TOTAL	801.7	893	10.2%
ENERGY.Burner_gas_consumption	405.29	406	0.17%
ENERGY.Boiler_gas_consumption	1857	1748	6.2%
PLANNING.Total_pigs	1024	899	13.9%
PROD.Total_kg	87531	103800	15.7%
PROD.Distributed_kg	38158	49173	22.4%

4.2. Validation of traceability and transparency by blockchain

The traceability platform developed by Stelviotech has proven to be a highly effective tool, integrating all critical information related to the end products across the agri-food value chain. It offers both companies—DIMITRA and PORTESA—the capability to monitor their production processes from origin to end consumer, whether that origin is the farm or the field. Each stage is meticulously documented, while the system also provides producers with full control over which information is shared externally. As illustrated in Figure 7 and Figure 8 for DIMITRA, the platform outlines each workflow step-by-step, not only aligning with the companies' existing processes but also enhancing them through improved structure and visibility. The level of workflow detail depends on the initial input provided during the setup of each product type. During testing with products from both companies, the platform successfully tracked every step of the production chain, offering fast and comprehensive access to relevant information.

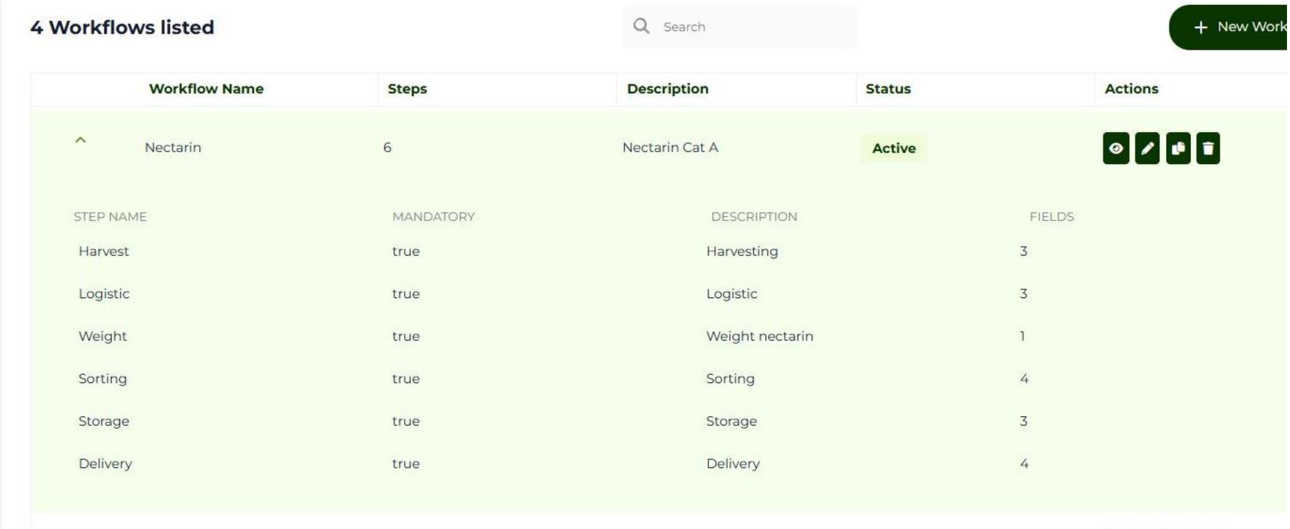

Figure 7: Workflows of the different products

Nonetheless, while the platform is capable of storing extensive details on processes and certifications, it does require users to be familiar with computer systems and to dedicate time to inputting data for each product and process.

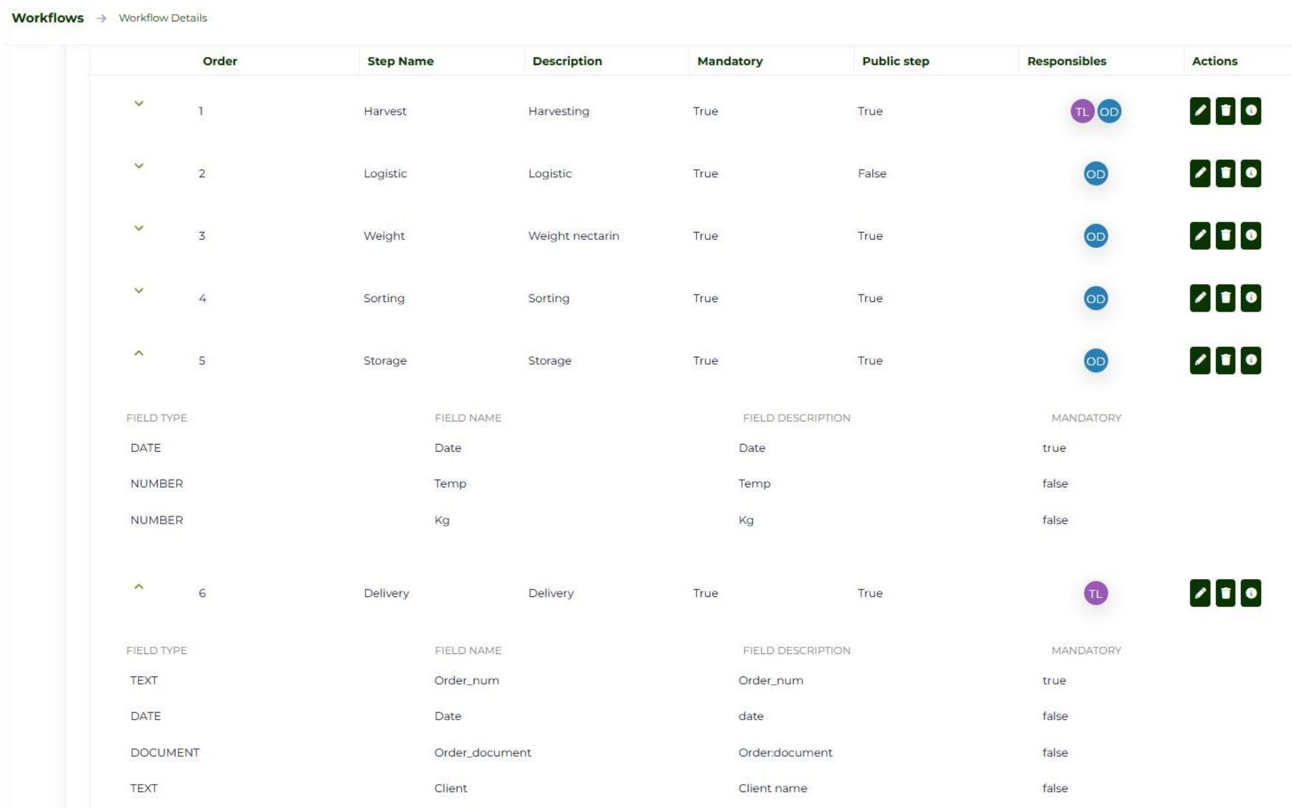

Figure 8: Detailed workflow of a product with the contained data

Among the two cases, the platform proved particularly valuable for PORTESA, Cartesa, and Aire Sano. In this context, traceability was exceptionally precise, as each pig was assigned a unique identification code, allowing end products to be traced directly back to the individual animal. In contrast, the fruit sector presents inherent limitations: traceability can only reach the level of the field, not the specific tree. Although this was an expected constraint, it prevents the traceability system from achieving full granularity. Importantly, this limitation arises from the nature of the product itself, not from any deficiency in the platform's capabilities.

4.3. Validation of biomass processing

In the biomass processing use case, neither of the two companies has yet implemented the proposed methods in practice. The existing infrastructure currently lacks the capacity to support such methods, meaning that the results related to biomass remain at an experimental stage and are primarily based on the collaborative work conducted with CVR.

For the PORTESA case within the BBTWINS project, a Digital Twin was developed to simulate the operation of a biogas production facility that processes pig waste. While the model is designed to replicate a realistic biomass processing setup, it is important to note that no such biogas facility currently exists on-site at PORTESA. This absence of an operational benchmark limits the possibilities for traditional validation using in-situ measurements. Consequently, the only viable approach for evaluating the Digital Twin's performance is through comparison with experimental data provided by CVR, along with feasibility estimations presented in the BBTWINS deliverable D6.4.

Figure 9: Digital Twin of the Biogas Plan

This study presents a focused comparative analysis between the outputs of the simulation model and the feasibility findings of the project, specifically concerning the anaerobic digestion of pig manure. The objective is to assess the Digital Twin's predictive capabilities in estimating key processing outcomes such as biogas yield, organic matter conversion, and energy output. By comparing the model's simulated results with the techno-economic parameters and performance indicators documented in D6.4, this analysis serves as an initial validation step and offers insight into the potential accuracy and viability of the proposed biomass processing solution. According to the simulation model, processing 1,000,000 tons of pig manure yields approximately 6.98 million m^3 of biogas, with a corresponding methane production of 3.10 million m^3 across all pig-related inputs. This closely aligns with BBTWINS estimates, which project a total annual yield of 19.7 million m^3 of biogas from pig manure, wastewater sludge, and leguminous residues at regional scale. Given that the simulation likely models a single-facility scenario, the biogas yield per ton of manure is consistent with that found in the deliverable, validating the scalability of the modelled approach.

In terms of organic content, the model reports 123,190 tons of organic matter and 172,000 tons of total solids in pig manure. These values support the substrate quality assumptions in BBTWINS, which identify pig manure as a high-value feedstock for anaerobic digestion due to its rich organic load and favorable bioconversion characteristics.

Energy-wise, the simulation estimates a biomethane energy output of 1.69 million KJ post-purification and 45.06 million kWh of electricity from cogeneration. These results are in line with the deliverable's economic evaluation, which confirmed the financial viability of biogas plants, reporting a Net Present Value of €24 million, an IRR >15%, and a payback period of just 1.2 years.

This comparison affirms the technical consistency between digital simulation models and feasibility studies, demonstrating that pig manure offers a reliable substrate for biogas production both in theoretical and practical applications. The coherence of the results strengthens the case for scaling up digital twin models in real-world biomass processing and supports further investment in manure-to-energy conversion systems.

In parallel to the biogas feasibility studies, CVR conducted a series of combustion experiments using pruning residues, with a particular focus on peach tree biomass. These tests aimed to assess the potential of this underutilized resource as a solid biofuel, through its densification into briquettes and subsequent combustion performance. Pruning residues, despite their abundance in Mediterranean agricultural systems, remain largely untapped due to logistic, economic, and technological barriers. CVR's trials sought to overcome some of these limitations by producing 20 kg of briquettes from residual peach pruning using a pilot-scale RUF-4 briquetting system. The briquettes were subjected to a suite of analyses, including proximate and ultimate composition, heating values, and physical characterization.

The combustion trials were carried out using a 25-kW downdraft wood gasification boiler under controlled operating conditions. Results indicated that peach pruning briquettes performed satisfactorily in terms of combustion behavior. The flue gas temperature reached up to 534 K, and emissions of CO were notably low (285 mg/m^3 @ 6% O_2), significantly outperforming pine wood briquettes which exhibited much higher CO levels. This suggests a more complete combustion of peach biomass under similar conditions. However, the nitrogen content of the peach pruning, likely due to the presence of bark, leaves, and fertilized tissues, led to a higher NOx emission (433 mg/m^3 @ 6% O_2), compared to pine briquettes (169 mg/m^3). Nonetheless, particulate matter emissions and TOC remained within acceptable limits and similar across both fuels.

These findings confirm that pruning waste, particularly from peach orchards, can be effectively valorized as a solid biofuel through briquetting and combustion. Despite some challenges related to fuel stabilization and combustion controls, such as oxygen fluctuation and fuel loading, these residues present an environmentally and economically viable alternative to conventional woody biomass. This supports the BBTWINS objective of promoting circular economy models by leveraging overlooked biomass streams and demonstrates the technical feasibility of decentralized, small-scale combustion systems for agricultural waste recovery.

5. Measurement for Operational success

The digital tools developed within the scope of the BBTWINS project represent a significant step forward for companies aiming to modernize, optimize, and future-proof their value chains. These tools, ranging from advanced simulation models to traceability platforms, offer powerful support mechanisms for both operational supervision and strategic decision-making. In an increasingly data-driven and competitive agri-food industry, digital technologies are no longer optional—they have become essential instruments for improving productivity, ensuring compliance, and fostering sustainable growth.

However, the full potential of digital tools can only be unlocked when they are systematically validated and embedded within a framework that supports performance monitoring and continuous improvement. As discussed in Chapter 4, validation is the foundation for trust in the digital tools' outputs, ensuring that they accurately reflect real-world systems and are capable of guiding decisions with confidence. Building upon validation, the next crucial step in leveraging digital transformation is the definition and implementation of *Key Performance Indicators* (KPIs). KPIs serve as quantifiable metrics that allow companies to set targets, monitor progress, and evaluate success. They enable management teams to identify inefficiencies, prioritize interventions, and track improvements over time. Without such benchmarks, even the most sophisticated digital solutions may fall short of delivering tangible business value (Collins et al., 2016).

In the context of the BBTWINS project, KPIs were designed not only to measure general operational efficiency but also to provide tailored insights for the specific use cases developed: process and logistics optimization in the fruit and meat sectors, and biomass valorization through digital twins. These indicators help bridge the gap between simulation and reality, enabling a feedback loop in which real-world performance refines digital models, and improved models support more accurate forecasting and optimization.

The process and logistics optimization use case, for example, simulates end-to-end operations in both animal food production and fruit supply chains. In the meat sector, the digital twin captures the full production cycle—from feed mill operations, animal farming, slaughtering, and processing—to forecast labor requirements, predict losses, and align production with market demand. Similarly, in the fruit sector, the DT models every phase of the ordering and distribution process, allowing producers to plan more accurately, reduce overproduction, and minimize waste. When integrated with KPI frameworks, these simulations become dynamic decision-support tools, continuously guiding operational improvements based on measurable goals. Table 3 below outlines a selection of KPIs identified as relevant across all use cases developed under the project. The presented KPIs are greater described in the Annex, it includes all the formulas for each KPI along with a more detailed description and information for the relevant parameters or supporting elements as mentioned on chapter 3. These indicators support multi-level evaluation—

from machine-level performance to supply chain traceability—and can be tailored to specific production environments:

Table 3: List of KPIs for operational success measurement

KPIs	Name	Description
1	Availability	The percentage of actual time a machine is available
2	Production	The efficiency of production vs. malfunction-caused interruptions
3	Worker efficiency	The efficiency of a worker's attendance in production
4	Effectiveness	How effective a machine can be during the production time, measured by the ratio of planned target cycle time to actual cycle time
5	Importing time	The time duration for the importing procedure
6	Exporting time	The time duration for the exporting procedure
7	Travel time	The travel time required from point A to point B
8	Traceability Coverage	The detail of the traceable steps
9	Update Frequency	The frequency real time data are recorded and uploaded to the database
10	Time to Trace request	How long it takes to trace a specific step of the process
11	Waste ratio	The percentage of bad to good products
12	First time quality	The percentage of good quality parts going through the manufacturing process in the first time
13	Energy consumption	The amount of energy required for the operation to run

Looking ahead, the KPIs presented in Table 3 serve as more than just operational metrics; they form the backbone of a data governance strategy that supports scalability, innovation, and long-term impact. By continuously aligning digital twin outputs with these indicators, companies can not only track deviations and inefficiencies but also anticipate future challenges, simulate alternative scenarios, and make proactive adjustments to their production systems. Furthermore, when KPIs are integrated into digital dashboards and visualized in real-time, they become powerful tools for cross-functional coordination—enabling operations managers, quality controllers, sustainability officers, and logistics teams to work from a shared set of insights. This convergence of roles and data fosters a culture of transparency and accountability, which is critical in sectors like agri-food, where traceability and compliance are closely investigated. The use cases explored within BBTWINS show that while digitalization requires upfront investments in infrastructure, validation, and user training, it yields significant returns when paired with well-defined performance targets. It also encourages a shift in mindset—from reactive management to predictive and adaptive planning. As the digital transition progresses, future iterations of the project could explore more advanced forms of performance measurement, such as AI-driven anomaly detection, real-time feedback loops, and predictive maintenance scheduling.

6. Result Analysis

The implementation and validation of digital tools within the BBTWINS project yielded promising and tangible outcomes across the three use cases: Process and Logistics Optimization, Traceability and Transparency, and Biomass Processing. These results not only confirm the feasibility of Digital Twins (DTs) and traceability platforms in real-world agri-food environments but also demonstrate their capacity to support data-driven decision-making, operational efficiency, and value chain sustainability.

The digital twins developed for DIMITRA and the PORTESA-CARTESA-Aire Sano ecosystem successfully simulated complex production and logistics workflows, achieving a high level of fidelity when compared to actual operational data. For DIMITRA, the DT model captured key elements of internal operations including worker movement, energy flows, materials usage, and waste generation. Among the seven parameters validated, six exhibited deviations under the acceptable 20% threshold, with energy production and waste output showing deviations as low as 1.3% and 1.1% respectively. Although the energy consumption value deviated by 21.2%, this was attributed to the model's current limitations in simulating the full breadth of fruit varieties and their respective processing needs. These findings confirm that the DT effectively represents DIMITRA's internal environment and can be reliably used for forecasting, resource planning, and production optimization. Similarly, the PORTESA use case—due to its vertically integrated structure, which required multiple digital twin models across the value chain, including fattening farms, feed mills, meat processing facilities, and distribution stages. The CARTESA DT, which focused on energy and production metrics, showed strong alignment with real-world values. Burner and boiler gas consumption had minimal deviations (0.17% and 6.2% respectively), and the number of pigs processed (13.9% error) and total product weight (15.7% error) were also well within the defined tolerance. The only parameter exceeding the threshold was distributed product weight, with a 22.4% deviation. This was largely attributed to dynamic and non-linear factors in the logistics chain that are difficult to simulate with current inputs, such as fluctuating demand, third-party scheduling, and transport variability.

Beyond production modelling, the traceability and transparency platform—powered by blockchain and developed by Stelviotech—demonstrated strong functionality and real-time reliability. For PORTESA and its affiliated entities, the platform enabled precise traceability from the individual animal to the final meat product. This level of granularity significantly enhances regulatory compliance, consumer trust, and internal quality assurance processes. By contrast, in the DIMITRA case, traceability was inherently limited to the field level due to the characteristics of orchard-based agriculture. Despite this sectoral constraint, the platform successfully mapped operational workflows and allowed dynamic data access for producers, clients, and consumers. Both organizations emphasized the platform's value in streamlining information flows and improving transparency, though they also noted the importance of addressing barriers related to staff training and time allocation for data entry.

The use case on biomass processing remains in a pre-implementation phase but has laid valuable groundwork for future circular economy initiatives. PORTESA's digital twin simulating a biogas plant based on pig waste was validated using experimental data from CVR, as no physical facility currently exists. The simulation suggested that the integration of biogas as an energy source could be technically viable and economically beneficial, especially when paired with complementary renewable sources such as photovoltaics. In DIMITRA, the biomass simulation explored the valorization of fruit waste into functional compounds, including polyphenols, pectin, and dietary fiber. While infrastructure for such processes is not yet in place, the DT outputs provided insight into the potential for developing nutraceutical and bio-based product lines from currently underutilized side streams.

Overall, the validation activities across the three use cases produced four key observations. First, the digital twins demonstrated consistent and reliable performance, with most parameters falling within a 20% deviation from real-world data. This confirms their robustness for simulating operational environments and generating performance forecasts. Second, the tools proved scalable and adaptable to different enterprise sizes and organizational structures—from the cooperative model of DIMITRA to the vertically integrated system of PORTESA. Third, when linked to a clear KPI framework, the tools provided not just simulations, but also actionable insights for production efficiency, energy optimization, and waste minimization. Finally, the project revealed important sector-specific challenges: in particular, the limitation of traceability in orchard-based agriculture and the need for more granular logistics data in meat distribution scenarios. These findings underscore that while digital tools offer high potential, their effectiveness depends on the ecosystem in which they are deployed. Factors such as digital readiness, data availability, infrastructure maturity, and user training all play critical roles in shaping outcomes. In both pilot cases, the initial investment in modelling and validation has already yielded operational insights, laying the foundation for broader digital adoption. The implementation of KPIs further supports this transition, enabling ongoing performance monitoring and continuous improvement strategies.

7. Optimization

The integration of digital technologies has become indispensable for the effective organization and strategic management of modern companies. As demonstrated in the previous chapter, the digital tools developed within the BBTWINS project—particularly the Digital Twin platforms—have been validated to deliver results that closely mirror real-world operations. This high degree of accuracy confirms that these tools are not merely useful for operational oversight, traceability, or waste monitoring, but can be extended to support advanced optimization and decision-making scenarios.

Rather than relying solely on conventional data analysis or static management routines, companies now have the opportunity to simulate proposed changes within a risk-free digital environment. Through the application of Digital Twins, businesses can evaluate how even minor adjustments in their value chains may impact overall performance—both operationally and financially. These simulated interventions can range from simple changes, such as reallocating tasks or hiring an additional employee, to more substantial strategic decisions like investing in infrastructure upgrades or expanding into new markets. By forecasting outcomes in a virtual setting, companies significantly reduce risk and gain a deeper understanding of the consequences associated with various decisions. This foresight enables data-driven planning and improves the precision of managerial actions.

In the context of the BBTWINS project, this optimization capability was practically demonstrated in collaboration with DIMITRA. Although the changes tested were modest in scale, the impact proved to be meaningful. Through structured consultations with DIMITRA's personnel, several operational bottlenecks were identified—specific points in the workflow that hindered efficiency or slowed throughput. The Digital Twin platform was then used to simulate various interventions aimed at improving these weak links.

Simulation.ObjectType	Default	Test	Column1
COSTS.Personnel	3742,453997	3690,722169	1,382296964
COSTS.Energy	23804,04213	23800,979	0,012868114
COSTS.Energy_balance	-3125,537751	-3122,47462	-0,098003333
COSTS.Materials	35640,83	35639,25	0,004433118
ENERGY.Conveyor_belt	627,5870325	627,5641341	0,003648636
ENERGY.Washing	2368,86039	2368,631687	0,009654562
ENERGY.Brushing	1614,850378	1614,810415	0,002474717
ENERGY.Artificial_vision	753,7692347	753,7879464	0,002482424
ENERGY.Sorter	1917,300189	1924,062666	0,352708283
ENERGY.Paletizer	58,25	38,83333333	33,33333333
ENERGY.Chambers	49046,4486	49042,07477	0,008917734
ENERGY.TOTAL_SIM_consumption	56400,06582	56379,64495	0,036207182
ENERGY.Chamber_2	20507,43925	20501,85047	0,027252476
ENERGY.Chamber_5	554,9906542	555,4766355	0,087565674
ENERGY.Chamber_6	1605,196262	1605,682243	0,030275507
ENERGY.Chamber_9	3221,327103	3221,570093	0,007543185
ENERGY.Waiting_chamber	13	9,88	24
ENERGY.TOTAL_NET_consumption	-99787,69055	-99808,11142	-0,020464322
MATERIAL.Filled_wooden_boxes	20990	20988	0,009528347
MATERIAL.Plastic_layers	20990	20988	0,009528347
MATERIAL.Box_stickers	20990	20988	0,009528347
MATERIAL.Fruit_stickers	461806	461804	0,000433082
TIMES.Unloading_Weighing(d)	0,84155197	0,75319384	10,49942645
TIMES.Sort_line	25,02280093	25,02041667	0,009528347
TIMES.Palletisation	1,451678241	1,451513889	0,011321507
TIMES.Palletiser	0,970833333	0,647222222	33,33333333
WEIGHT_LOSS.Total	13444,08001	13443,71792	0,002693305
WEIGHT_LOSS.Original_weight	105276,864	105262,916	0,013248875
WEIGHT_LOSS.Real_weight	91832,78399	91819,19808	0,014794183

Figure 10: Comparison of the default and test case presenting the effect of hiring two employees

One of the initial scenarios tested involved accelerating the pace of selected internal procedures. Unsurprisingly, the simulation revealed a significant improvement in productivity, as faster operations naturally allowed a greater volume of goods to be processed within a given time frame. However, this result also exposed a critical limitation: the pace of human labor is not uniform and can fluctuate due to numerous factors such as fatigue, motivation, or external disruptions. Recognizing this variability, the team explored a more stable and scalable solution—strategically hiring two additional employees to support specific operational areas. The simulated outcome of this intervention, illustrated in Figure 10, showed notable gains in throughput and overall performance, reinforcing the value of Digital Twins as a tool for evaluating personnel strategies and optimizing resource allocation.

Among all the parameters evaluated through the Digital Twin simulation, five stood out for their significant impact and are summarized in Table 4. Notably, hiring two additional employees led to a 1.38% reduction in personnel costs. Although counterintuitive at first glance, this decrease is attributed to faster task completion, which in turn results in lower overall energy consumption and more efficient shift utilization. For instance, energy usage in the palletizer unit dropped by 33.34%, while energy consumed in the waiting chamber decreased by 24%. Time efficiency also improved considerably. The unloading and weighing process duration was reduced by 10.5%, and the palletizing time saw a substantial decline of 33.34%. These improvements translate into a leaner, more productive workflow, where more work can be completed within the same time frame. As a result, operational margins increase, and the return on investment for the additional hires becomes not only justified but strategically advantageous. However, it is important to keep in mind that these figures are the results of adjusting just two parameters, any other changes along with the hires will lead to different results. So, it is important to double check and test all the affected parameters before implementing any of these changes.

Table 4: Mostly affected results from the optimization method for the case of DIMITRA

Simulation.ObjectType	Default	Test	Column1
COSTS.Personnel	3742,453997	3690,722169	1,38%
ENERGY.Paletizer	58,25	38,83333333	33,34%
ENERGY.Waiting_chamber	13	9,88	24%
TIMES.Unloading_Weighing(d)	0,84155197	0,75319384	10,5%
TIMES.Palletiser	0,970833333	0,647222222	33,34%

Ultimately, this example highlights how Digital Twin technologies empower companies to pre-test potential improvements in a controlled, data-rich environment before committing real-world resources. By bridging the gap between intention and implementation, these tools not only enhance operational agility but also support long-term strategic planning grounded in evidence rather than intuition.

8. Conclusions

The implementation and validation of the digital tools developed under the BBTWINS project have demonstrated that Digital Twins and blockchain-based traceability platforms can serve as powerful enablers of transformation within the agri-food sector. Through detailed modelling, real-world testing, and performance evaluation using clearly defined KPIs, the project has confirmed the feasibility and utility of these technologies across two distinct and representative value chains—fresh fruit (DIMITRA) and pork production (PORTESA, CARTESA, AIRE SANO).

The digital twins exhibited high accuracy in replicating operational processes, with most simulation outputs deviating less than 20% from actual measured data. This confirms the DTs' suitability as tools for production forecasting, energy efficiency monitoring, logistics planning, and resource allocation. Even in more complex or variable parameters, such as energy consumption or product distribution, the deviations were explainable and within a reasonable margin, highlighting the robustness of the modelling approach.

The traceability system further enhanced operational transparency and control. In the meat sector, full traceability from animal to end product was achieved, providing a competitive advantage in terms of regulatory compliance and consumer trust. While traceability in the fruit sector faced structural limitations, the system still improved internal logistics and data access, supporting better-informed decisions.

Although the biomass processing component remains at an early stage of development, it represents a critical step toward the adoption of circular economy practices. The simulations have revealed viable pathways for valorizing agri-food residues, offering insight into the design of future infrastructure and business models.

Importantly, the project has shown that digitalization cannot succeed in isolation. Beyond technical validation, successful implementation requires investment in user training, digital literacy, data integration, and change management. Organizational readiness and cross-functional collaboration are essential for ensuring that these tools are embedded effectively and deliver long-term impact.

In conclusion, BBTWINS provides a replicable, scalable framework for integrating digital innovation into bio-based value chains. The tools developed have proven their reliability, adaptability, and relevance, and they have the potential to reshape operational practices, enhance sustainability, and foster resilience in Europe's agri-food sector. As the project progresses, efforts should now focus on maximizing the tools' adoption, refining user interfaces, and expanding the use cases to include new sectors and geographies. With continued collaboration among technology developers, producers, researchers, and policy stakeholders, BBTWINS can serve as a blueprint for the digital transformation of the European bioeconomy.

Annex

Table 1.

KPI name	Availability
Type	Production
Function	$A = \frac{APT}{PBT} * 100\%$
Target and description	The percentage of actual time a machine is available. It represents the portion of time used for processing compared to the total time that includes AUST, delay time and down time.
Data necessary to calculate the KPI	1. *APT = Actual Production Time* 2. *PBT= Planned busy time*

Table 2.

KPI name	Technical efficiency
Type	Production
Function	$TE = \frac{APT}{APT + ADOT} * 100\%$
Target and description	The efficiency of production vs. malfunction-caused interruptions. It represents the relationship between APT and the sum of APT and ADOT that includes times of malfunction-caused interruptions.
Data necessary to calculate the KPI	1. *APT = Actual Production Time* 2. *ADOT = Actual unit down time*

Table 3.

KPI name	Worker efficiency
Type	Production
Function	$WE = \frac{APWT}{APAT} * 100\%$
Target and description	The efficiency of a worker's attendance in production, measured by the relationship between the actual personnel's work time (APWT) related to production orders and the actual personnel's attendance time (APAT).
Data necessary to calculate the KPI	1. *APWT = Actual Personnel Work Time* 2. *APAT = Actual Personnel attendance time*

Table 4.

KPI name	Effectiveness
Type	Production
Function	$E = \frac{PRI}{\frac{APT}{PQ}} * 100\% = \frac{PRI * PQ}{APT} * 100\%$
Target and description	How effective a machine can be during the production time, measured by the ratio of planned target cycle time (represented as planned runtime per item (PRI)) to actual cycle time (expressed as APT divided by produced quantity (PQ)).
Data necessary to calculate the KPI	1. *PRI = Actual Personnel Work Time* 2. *APT = Actual Personnel attendance time* 3. *PQ= Produced Quantity*

Table 5.

KPI name	Importing time
Type	Production
Function	$Importing\ time = \frac{Products\ (Kg) per\ receipt}{\frac{kg}{hr}\ we\ can\ transfer}$
Target and description	The time efficiency optimization of the importing procedure.
Data necessary to calculate the KPI	1. Kg of products per receipt 2. How many Kg of fruits we can handle per hour

Table 6.

KPI name	Exporting time
Type	Production
Function	$Exporting\ time = \frac{Products\ (Kg)\ per\ order}{\frac{kg}{hr}\ we\ can\ transfer}$
Target and description	The time efficiency optimization of the exporting procedure.
Data necessary to calculate the KPI	1. Kg of products per order 2. How many Kg of fruits we can handle per hour

Table 7.

KPI name	Importing time
Type	Production
Function	$Operation\ time = \frac{Products\ (Kg)\ per\ variety}{\frac{kg}{hr}\ we\ can\ transfer}$
Target and description	Aiming to optimize the procedure in order to reduce time duration
Data necessary to calculate the KPI	1. Kg of products per variety 2. How many Kg of fruits we can handle per hour

Table 8.

KPI name	Time from point A to point B
Type	Logistics
Target and description	To evaluate the time to transfer the products between two points
Data necessary to calculate the KPI	the actual times (min) for the truck to move directly between two points

Table 9.

KPI name	Traceability Coverage
Type	Logistics
Target and description	The level of traceability. How many steps of the process can be traced back to initial form of the product
Data necessary to calculate the KPI	

Table 10.

KPI name	Update Frequency
Type	Logistics
Target and description	The frequency real time data are recorded and uploaded to the database
Data necessary to calculate the KPI	

Table 11.

KPI name	Time to Trace request
Type	Logistics
Target and description	How long it takes to trace a specific step of the process.
Data necessary to calculate the KPI	

Table 12.

KPI name	Actual to planned scrap ratio (SQR)
Type	Quality
Function	$SQR = \frac{SQ}{PSQ} * 100\%$
Target and description	The relationship of the actual SQ and the PSQ, indicating how much scrap is produced compared with the expected value. Clearly a lower value of SQR is preferred since it implies less scrap than expected. However, a constant low SQR value may indicate that the PSQ is too high, which may result in inefficient resource allocation.
Data necessary to calculate the KPI	1. *SQ = Scrap Quantity* 2. *PSQ = Planned Scrap Quantity*

Table 13.

KPI name	Scrap ratio (SR)
Type	Quality
Function	$SR = \frac{SQ}{PQ} * 100\%$
Target and description	The relationship between the SQ and PQ.
Data necessary to calculate the KPI	1. *SQ = Scrap Quantity* 2. *PQ= Produced Quantity*

Table 14.

KPI name	Rework ratio (RR)
Type	Quality
Function	$RR = \frac{RQ}{PQ} * 100\%$
Target and description	The percentage of RQ among PQ.
Data necessary to calculate the KPI	1. *RQ = Rework Quantity* 2. *PQ= Produced Quantity*

Table 15.

KPI name	First time quality (FTQ)
Type	Quality
Function	$FTQ = \frac{GQ}{PQF} * 100\%$
Target and description	The percentage of good quality parts going through the manufacturing process in the first time.
Data necessary to calculate the KPI	1. *GQ = Good Quantity* 2. *PQF= Produced first process quantity*

Table 16.

KPI name	Quality buy rate (QBR)
Type	Quality
Function	$QBR = \frac{GQ + RQ}{PQ} * 100\%$
Target and description	The overall percentage of good quality parts after reworks.
Data necessary to calculate the KPI	1. *GQ = Good Quantity* 2. *PQ = Produced Quantity* 3. *RQ = Rework quantity*

Table 17.

KPI name	Energy consumption
Type	Costs
Function	
Target and description	to calculate the energy consumption of the main units/subunits of the production line
Data necessary to calculate the KPI	The actual measured kWh of the production line units

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