Enhancing Interaction with Data Lakes Using Digital Twins and Semantic Blueprints

Spyros Loizou[a], Michalis Pingos[b] and Andreas S. Andreou[c]
Department of Computer Engineering and Informatics, Cyprus University of Technology, Limassol, Cyprus

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Abstract: Advanced analytical techniques and sophisticated decision-making strategies are imperative for handling extensive volumes of data. As the quantity, diversity, and speed of data increase, there is a growing lack of confidence in the analytics process and resulting decisions. Despite recent advancements, such as metadata mechanisms in Big Data Processing and Systems of Deep Insight, effectively managing the vast and varied data from diverse sources remains a complex and unresolved challenge. Aiming to enhance interaction with Data Lakes, this paper introduces a framework based on a specialized semantic enrichment mechanism centred around data blueprints. The proposed framework takes into account unique characteristics of the data, guiding the process of locating sources and retrieving data from Data Lakes. More importantly, it facilitates end-user interaction without the need for programming skills or database management techniques. This is performed using Digital Twin functionality which offers model-based simulations and data-driven decision support.

1 INTRODUCTION

Nowadays, in the era of Big Data, a substantial volume and variety of data generated from various sources necessitate storage in new Big Data architectures. Data visualization represents data in a systematic form, including attributes and variables for the unit of information. Visualization data allows users and businesses mash up data sources to create custom analytical views (Gupta et al., 2022). A Digital Twin (DT) is a virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning and reasoning to support decision-making. In addition, a DT can also facilitate predictions about how an asset or process will evolve or behave in the future (Rasheed et al., 2020).

The analysis of massive amounts of data requires advanced analytical techniques for processing and advanced decision-making strategies. As the amount, variety, and speed of data increases, lack of confidence in the resulting analytics process and decisions grows. In comparison to traditional data techniques and platforms, artificial intelligence techniques such as machine learning, natural language processing, and computational intelligence, provide more accurate, faster, and scalable results in big data analytics (Hariri et al., 2019).

Despite the substantial and transformative solutions suggested in recent years, such as metadata mechanisms within the realm of Big Data Processing and Systems of Deep Insight, effectively handling the extensive data generated by diverse and varied sources remains a complex and unresolved issue. This paper addresses this challenge and focuses on visual representation and interactive techniques to transform primary, raw data residing in Data Lakes (DLs) to meaningful data, which may be utilized by end users.

The contribution of this paper lies with the proposition of a framework and a dedicated semantic enrichment mechanism structured around data blueprints to facilitate interaction with DLs. A suggested technique to improve metadata in a DL environment is called "data blueprint," which uses

[a] https://orcid.org/0009-0009-3433-3245
[b] https://orcid.org/0000-0001-6293-6478
[c] https://orcid.org/0000-0001-7104-2097

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semantics as a framework for describing data sources before they are included in a DL. The framework includes data specific characteristics and guides the process of locating the sources and retrieving data residing in DLs with the functionality and benefits of a DT environment.

The rest of the paper is structured as follows: Section 2 discusses related work and provides the technical background in the areas of data processing and visualization, DTs and DLs. Section 3 presents the proposed framework and describes how blueprints and their extended data characteristics are integrated in processing and analysis steps to facilitate decision support. Section 4 demonstrates the proposed approach using a real-world case-study performed in a smart manufacturing environment and more specifically using real-world data collected at a local poultry meat factory Paradisiotis Group Ltd (PARG). Finally, Section 5 concludes the paper and highlights future work steps.

2 TECHNICAL BACKGROUND/ RELATED WORK

This section briefly describes the technical foundations of data processing, DTs and DLs, as well as visualization platforms that use blueprints to process data. To the best of our knowledge, no research has been documented as to how to combine extended features and data blueprints for customized smart analytics using graphical environments for interactive, visual, smart data processing in the literature. In the world of Big Data, data visualization tools and technologies are the challenges tackled in different papers focusing on how to analyse massive amounts of information and make data-driven decisions. By introducing traditional visualization techniques and extending some of them for handling large data, talking about the difficulties associated with big data visualization, and examining technological advancements in big data visualization, Gupta et al., (2022) present new techniques and advancements in the field.

2.1 Digital Twins

Generally, DT is a physical product or process that exists in the real world and is used for operations as its practically identical digital counterpart. A DT controls the lifecycle of the IoT, minimizes defects, and optimizes errors to save money and time. Because a DT can stream, optimize, and analyze data in both the virtual and real worlds, it is a powerful technological tool. This work applies the concept of DTs using them to graphically represent data in real time and provide models for interaction and simulations.

Several papers address the problem of monitoring real-time data and optimization of graphical environments for interactive, visual smart data processing with characteristics based on blueprints. Automated analytics, semantics-based information fusion and process automation are among the targets for improving the performance of systems for real-time business intelligence (RTBI). Technologies like intelligent data analysis, soft computing and ontologies will play a major role in the development of RTBI (Azvine et al., 2006).

Pang et al. (2015) present an innovative Data-Source Interoperability Service (DSIS) that serves as a middleware for providing a querying and information integration service for heterogeneous data sources. The DSIS applies software agent technology that is capable of accomplishing tasks in an autonomous way without human intervention. Fuller et al. (2020) present the challenges, applications, and enabling technologies for Artificial Intelligence, IoT and DTs.

Kritzinger et al., (2018) aim to provide a categorical literature review of the DT in manufacturing and to classify existing publication according to their level of integration of the DT.

2.2 Data Lakes

Large volumes of organized and unstructured data at any scale can be stored centrally in a DL. A DL enables the storing of raw data in its original format, in contrast to typical databases or data warehouses, which demand that data be formatted before storing. DLs provide storage flexibility by enabling data to be stored without first defining a schema. This feature makes it possible to accommodate different formats and types of data from different sources.

Although DLs are very flexible, they must be managed carefully to avoid turning into "data swamps," which are places where data is disorganized, hard to locate and retrieve, and thus difficult to analyse in general. Data cataloguing, metadata management, and data governance policy establishment are essential procedures to handle this issue.

The authors in (Pingos and Andreou, 2022) propose a novel standardization framework that combines blueprint ontologies, DL architecture, and the 5Vs Big Data characteristics to address the

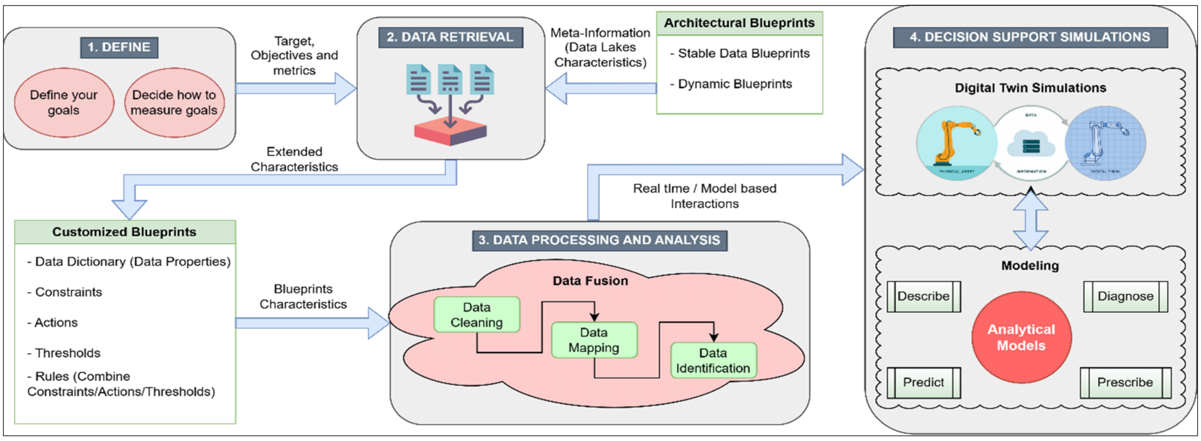


Figure 1: General architectural structure.

complex problem of dealing with heterogeneous data sources. Data blueprint is a proposed method to enhance the metadata within a DL environment, leveraging semantic as a guiding framework of describing data sources before they become part of a DL. The mechanism introduced in that work involves semantic structures and utilizes both the theory of Triples (subject-predicate-object) and the Resource Description Framework (RDF) to improve the organization, mapping, and retrieval of data stored in the DL. The semantic blueprints can be utilized with the combination of 5Vs characteristics of Big Data to improve the effectiveness and metadata quality within DLs, addressing challenges associated with managing and extracting meaningful information from large and diverse datasets.

The authors in Pingos et al., (2022) introduce DLMetaChain, an expanded DL metadata framework that combines IoT data with heterogeneous data sources. Blockchain technology has emerged recently as a potentially useful tool for resolving security and privacy issues, as well as for fostering trust between entities where it has either never been established or is non-existent. The expanded mechanism places a strong emphasis on creating an architecture that guarantees the integrity of the data in the DL.

The establishment of a metadata framework based on DL architecture as demonstrated in PARG factory is a noteworthy addition to the fields of data management and process mining. This novel structure, as put out (Pingos and Andreou, 2022) makes use of the idea of blueprints to methodically describe the data sources: Structure Blueprint (SB), Semi-Structured Blueprint (SEB) Unstructured Blueprint (UB) and manufacturing processes: Machine Blueprint (MB), Event Blueprint (EB) and Process Blueprint (PB). SB includes a metadata description of the correspondence pond which contains structured data. In addition to the SEB, there is also the UB, designed to capture and organize sources in the DL that lack a predefined data model. UB accommodates diverse and unstructured data types, enabling the system to handle information that may not conform to a specific format. Moreover, manufacturing processes are represented by the MB, EB and PB. These blueprints collectively provide a comprehensive framework for understanding and managing diverse aspects of the system's structure and processes. contributes to the construction of a comprehensive DL metadata history, presented in RDF (Resource Description Framework), offering a detailed and interconnected view of the system's evolving data landscape. This study, which focuses on a factory that breeds chicken and produces various forms of poultry meat, offers insightful information about business workflow analysis and operational assistance.

None of the studies on coupling DTs with DLs thus far has been concentrated on defining, linking, and analyzing data used for process and data modelling or computational enhancement through approaches that alleviate the need for expert knowledge. This paper addresses this challenge and provides the means for a totally different user experience based on visual querying and simulations, which is characterized by simplicity, self-explainability, ease of use and graphical ergonomics by extending data and process blueprints.

3 METHODOLOGY

The basic idea for using visual analysis is to present the data in a graphical and meaningful visual format so that the end-user can interact with it, learn from it, and make better decisions.

As previously mentioned, the main target of this paper is to utilize a DT in the form of a unified graphical and interactive dashboard to retrieve data from DLs based on their semantic annotation. This is performed by: (1) extending the applicability of data blueprints (SB, SEB, UB) and process blueprints (MB, EB, PB) (see previous section) and executing visual queries to deliver a graphical representation of structured, semi-structured and unstructured data retrieved from the DL based on their blueprint metadata history; (2) introducing a new semantic part, namely the Business Blueprint (BB), to describe the business processes associated with the data and which will guide more effectively the application of DT.

Figure 1 depicts the general architectural structure upon which this approach builds, which involves four distinct steps: (1) the definition of goals and how to measure them, (2) the mechanism for data retrieval, (3) the data processing procedures, and finally, (4) the interactive dashboard, which offers decision support simulations based on DTs using real-time data and four analytical models. A description of each of the steps follows:

Step 1: targets at enabling organizations to clearly define their goals and determine how to measure their progress towards those goals. This step essentially provides a structured approach to help organizations define their specific objectives and identify the metrics that will be used to evaluate success.

Step 2: essentially offers the means for data retrieval using latest advances on DLs that utilize architectural patterns, or as we call it, data blueprints. These blueprints provide the means for describing and characterizing data sources and the data they produce. The present paper, as mentioned earlier, extends these characteristics by suggesting a new, specialized form of a blueprint (BB) to support the interaction with a DT. The BB blueprint describes data properties revolving around manufacturing processes, rules, constraints, thresholds (for actuators) and actions (see Figure 2). To this end, we introduce also a Data Dictionary, which includes data properties, such as types, formats, units etc., and describes attributes and characteristics of the current data thus contributing to better understanding it and enabling efficient retrieval and processing. Rules combine constraints, actions and thresholds to provide guidelines for data handling and decision-making.

The DL architecture utilized in this paper is structured with ponds and puddles as described in (Pingos and Andreou, 2022). A dedicated data blueprint is used to describe every source that stores data in this DL, which is divided into two

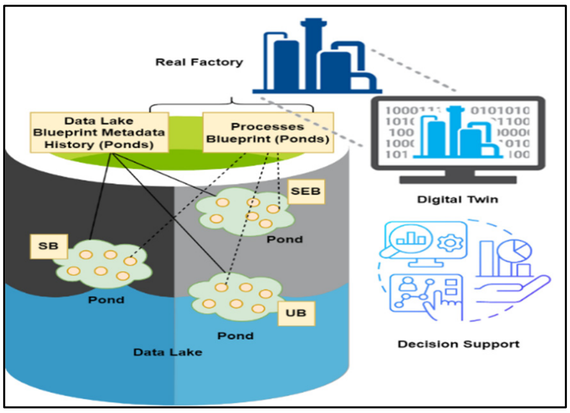


Figure 2: DT with the utilization of BB.

interconnected parts, the “Stable Data Blueprint” and the “Dynamic Data Blueprint”. The static one is stable over the time and records the name and type of the source, the type of data it produces, the value, velocity, variety, and veracity of data source. The dynamic characterizes the volume of data, the last source update, and the keywords of the source which are metadata characteristics may vary over time. A manufacturing production cycle consists of processes. Every process involves actions and events which are executed by a machine. All this information is described in a specific blueprint (Pingos and Andreou, 2022).

The blueprint descriptions produce an RDF ontology for the data sources written in XML format. RDF stands for Resource Description Framework and is used for describing resources usually found on the Web. RDF is designed to be read and understood by computer. The experiments that were conducted and will be presented later on code implemented in Python, while library *rdflib* was used for RDF manipulation. RDF triples were created to extend the data with additional characteristics.

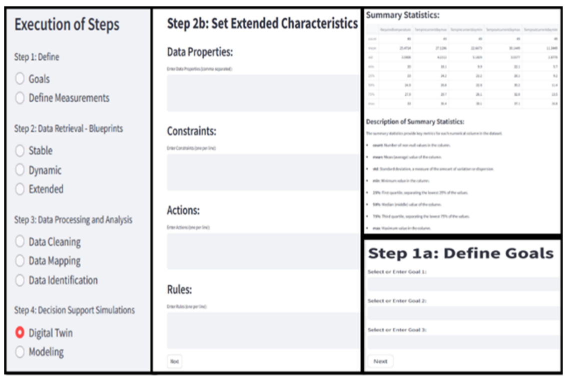


Figure 3: Graphical Dashboard available tools.

Step 3: supports Data Fusion using three techniques: (a) Data cleaning, (b) Data mapping, and (c) Data identification.

Data Cleaning aims at identifying and addressing errors, inconsistencies, and missing values in the underlying dataset. By applying data cleaning techniques, such as removing duplicate records and filling missing values, the quality and accuracy of the data is improved, ensuring also that the fused dataset is consistent.

Data Mapping is the process of integrating data from multiple sources based on common attributes. This activity establishes relationships and connections between datasets and confirms that the combined dataset includes an accurate representation of the topic, integrating relevant information from various sources (e.g. function *merge* in Python).

Data Identification finds and extracts major patterns, trends, and features from a dataset. Therefore, useful information and insights may be extracted from the fused data.

Overall, organizations can achieve efficient data fusion by utilizing techniques such as data cleaning, data mapping, and data identification. These techniques guarantee the useful value, consistency, and accuracy of the integrated dataset. The merged data offers a solid base for additional investigation, allowing organizations to collect perceptive knowledge and make decisions (see next step).

Step 4 conducts simulations for data-driven decision support. The DT concept, which offers a virtual representation of the data, facilitates the execution of such simulations and the interpretation of their results. Four analytical models may then be constructed, namely Describe, Diagnose, Prescribe, and Predict, to interact with the fused data produced in Step 3 during simulations. These models make use of the underlying dataset to identify problems, predict results, offer analytical insights and provide recommendations. More specifically, each model works as follows:

Describe Model: Aims to provide description of the system and the fused data to represent the elements, actions, and structure of the system.

Diagnose Model: Emphasizes on discovering and investigating problems, anomalies, or special patterns in the dataset. This model allows the identification of the basic reasons behind observed actions or results.

Prescribe Model: Generates prescriptive recommendations or actions based on meaningful insights. It offers practical recommendations to guide decision-making procedures.

Predict Model: Forecasts or predicts future behavior by using historical data and patterns. This model uses predictive analytics methods, like regression and time-series analyses, and machine learning algorithms, using the fused data and thus enables businesses to predict new developments.

Summing up, the proposed framework combines retrieval and processing of large volumes of structured, semi-structured, and unstructured data residing in DLs with a graphical interactive dashboard that offers DT-oriented simulations. Employing RDF, Python, and data fusion methods, the approach provides actions, constraints, thresholds and rules, described in the form of a dedicated blueprint architecture. Real-time analysis and decision-making are then facilitated with the creation of the Describe, Diagnose, Prescribe, and Predict models, which provide the means for efficient and accurate decision support.

4 DEMONSTRATION AND EXPERIMENTATION

This section presents the practical application of the proposed framework using real-world data collected in the poultry meat factory of PARG[4]. The factory breeds chicken in large capacity farms (20,000-30,000 chicks per farm) with automated ventilation and temperature systems, and a technologically advanced mill for mixing ingredients and producing chicken food. After a breeding cycle is concluded, slaughtering takes place at the factory and the meat produced is packaged with different ingredients according to orders placed, which are then sent to local supermarkets.

Figure 3 shows a collage of figures depicting different screens of the graphical interactive dashboard that was developed especially for the purpose of demonstrating the proposed approach. The dashboard essentially supports all steps of Figure 1 and offers DT capabilities. To this end, three real-world scenarios were constructed in close collaboration with engineers of the PARG factory to show how the framework may be employed so as to facilitate data-driven decision-making, enabling PARG to extract valuable insights, optimize processes, and enhance operational performance. The scenarios correspond to decisions regarding the ventilation process taking place within the breeding farms with different approaches as regards efficient control of inside temperature and energy

[4] https://paradisiotis.com/ (in Greek)

consumption. More specifically, the three scenarios investigated the optimal decision for lowering temperature in a breeding site by increasing the frequency of opening shutters, increasing the duration shutters stay open, and using a hybrid form combining the two. All scenarios were evaluated against successfully achieving the goal (lowering temperature), but at the same time energy consumption and, hence cost, was taken into consideration.

Step 1: Define
Options for predefined goals were available at this step including "Reduce Cost", "Improve Efficiency" "Improve Quality", "Reduce Waste", "Optimize Resource Usage", "Lower/increase temperature", etc. The users selected control the temperature control goal and set a specific (standard) breeding value for the farm environment (33°C). Then, the measurements and sensors that correspond to these goals were defined.

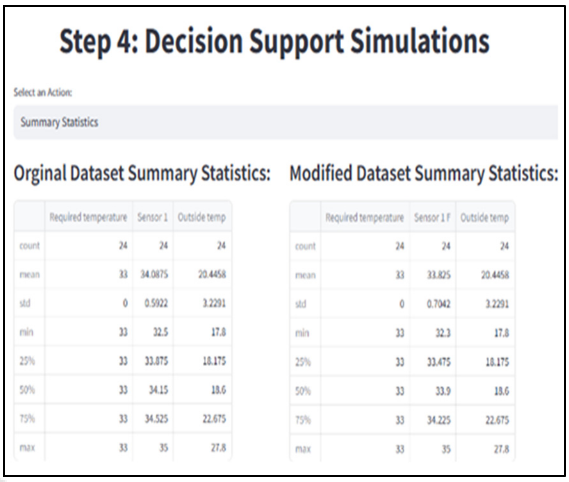
Step 2: Data Retrieval - Blueprints
Users stored relevant information in the DL based on the scenario needs, such as sensor readings for grow day 1… n (hourly for 24 hours), inside and outside temperature (2 sensors), humidity, CO_2, and static pressure. Sources and data were semantically annotated via the blueprints before being stored in the DL. Furthermore, users entered data properties, actions, constraints, and rules related to temperature control using the above parameter readings (further detailed information on related rules may not be disclosed to secure business processes privacy).

Step 3: Data Processing and Analysis
Users were able here to choose various data analysis tasks to execute using the uploaded data mainly through tabular formats.

Step 4: Decision Support Simulations
This step provided users with an extensive set of tools to profile, visualize, and actively manipulate temperature-related data to support decision-making related simulations. The system's user-focused design supports the main goal of utilizing a DT environment for data-driven decision-making in farming environments and enabled stakeholder1s to continually refine their temperature control strategies based on simulated scenarios and real-time insights. More specifically, the following sub-steps were taken:

4.1 Profile Data

Users profiled the data to learn more about the distribution, statistical measures, and important features of the columns related to temperature (see Figure 4, upper part, and lower left part). Understanding the basic conditions and variability in the farm environment was thus made easier by this profiling.



	Required temperature	Sensor 1	Outside temp
count	24	24	24
mean	33	34.0875	20.4458
std	0	0.5922	3.2291
min	33	32.5	17.8
25%	33	33.875	18.175
50%	33	34.15	18.6
75%	33	34.525	22.675
max	33	35	27.8

	Required temperature	Sensor 1 F	Outside temp
count	24	24	24
mean	33	33.825	20.4458
std	0	0.7042	3.2291
min	33	32.3	17.8
25%	33	33.475	18.175
50%	33	33.9	18.6
75%	33	34.225	22.675
max	33	35	27.8

Figure 4: Original vs modified summary statistics of data.

4.2 Edit Values

Users actively edited values within the selected data, allowing for hypothetical scenarios and "what-if" analyses. Using historical data, a temperature coefficient was calculated by dividing the difference of the inside temperature (before and after opening the windows) with the time the windows remained open. This coefficient was then used to estimate the increase/decrease of temperature during simulations. When users changed the value for the time windows remained open, the relevant effect on temperature was estimated based on the temperature coefficient (see right column at the lower part of Figure 4).

4.3 Visualize Data

The system provided interactive data visualization options, allowing users to create visual representations of temperature-related variables. The selected visualization types included bar charts, line charts, and scatter plots, which enabled users to identify patterns and trends in the data.

4.4 Perform Actions

Users employed various actions to simulate decision-making scenarios. The handling of numerical parameters, as in our case temperature, involves filtering and focusing on specific attributes of the data, using values that are "Greater than", "Average", "Equal to", "Less than or equal to", and "Greater than or Equal to", etc. a key value. Adjustments performed to the farm environment were triggered by studying the behavior of the filtering based on average temperature values and the corresponding changes in temperature thresholds were observed as previously described.

The main findings of the three scenarios may be summarized as follows:

Scenario 1: Increased Frequency of Window Openings

In this scenario, data is produced within the factory mainly by two systems: CUBORA, which is a fully operational heating control system requires for securing the healthy growth and well-being of chicks in the farms, and AGROLOGIC, which specializes in the field of automated climate controllers, feeding and weighing systems for the poultry. AGRO-LOGIC in PARG is being integrated with Chore Time controller and collects metrics from several remote sensors that are distributed into the farms, such as CO2, Temperature, Humidity, Air Static Pressure, and Light Intensity Level. All metrics are recorded in a database and are accessed through a Web application in real-time. Furthermore, images of the farms and/or equipment may be recorded for shift managers to inspect visually when appropriate. Finally, the system generates alerts if any of the metrics exceed pre-defined thresholds via an embedded GSM modem. The plant engineers, using the framework capabilities described in Step 4, decided to increase the frequency up to three times a day and investigate the impact of this decision in the simulated environment. It became evident that by enabling more frequent ventilation the system actively reacts to temperature average increases.

Scenario 2: Extended Duration of Window Openings

The second scenario investigated the effects of leaving the automated windows open for a longer amount of time (6 hours) while keeping the daily frequency stable (once). In Step 4, the users adjusted the duration settings to allow longer air conditioning times via the framework's user interface. Line charts depicting temperature and statistical summaries were consulted that highlighted the long-term cooling impact on farming operations. Figure 5 graphically depicts the outcome of this scenario (red color) contrasted with the outside temperature (blue) and the temperature achieved using the normal procedure (oceanic blue). The figure also shows the time windows remained open for the scenario and the normal procedure (area within dotted lines).

Scenario 3: Hybrid Approach

This scenario combined longer duration more frequently (twice a day for 3 hours each time). Again, using step 4 the users interacted with the framework to define that the system should automatically open the windows more often than before and for a little longer period. It became evident by using temperature visualizations in the hybrid scenario that there exists a complex relationship between frequency, duration, and temperature. Figure 6 shows the performance of each scenario tested with activation of windows openings indicated by circles.

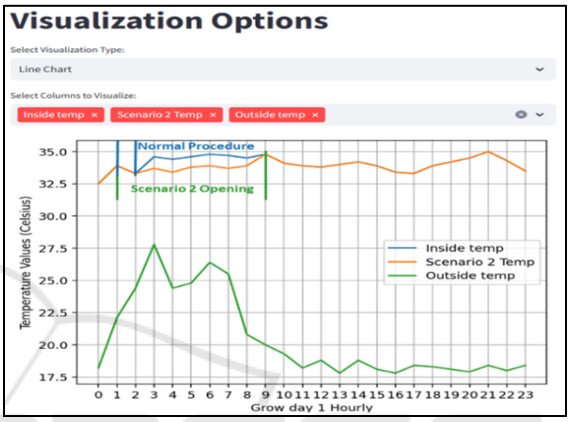


Figure 5: Behaviour of temperature based on window opening duration (scenario 2).

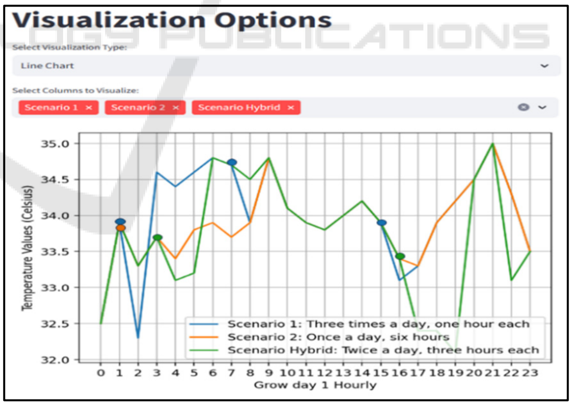


Figure 6: Combined effects of all scenarios on temperature values.

To optimize decision-making, the scenarios also considered energy consumption effects. The engineers evaluated the energy associated with each scenario as follows: The normal daily temperature control (NDTC) procedure involves opening windows once and starting a roof fan 2-3 times for some minutes. The purpose of the fan is to offer a more drastic solution to increasing or decreasing temperature so as to guide it to the optimal value of 33°C. More specifically, if outside conditions allow, the temperature of the breeding site can be controlled and brought to the optimal value using only the windows. Otherwise, is actually the fan that regulates the inside temperature. The fan, though, is a high energy consumption device, and, therefore, it should be used as little as possible. Each breeding cycle (50-60 days) consumes 3250KWh of energy based on the NDTC procedure. Using historical samples and measurements in the past, an average daily energy consumption was calculated, and this number was distributed between the opening of the windows and the operation of the fan with the support of site engineers. These figures were then used to calculate the energy cost of the decisions made according to the frequency and duration of the windows opening according to each scenario.

Based on the above, the engineer confirmed that all three scenarios were able to improve temperature and drive it close to the standard, desired value for the breeding site, which, as previously mentioned, should be 33 degrees Celsius. Scenario 1 lowers temperature from 34.08°C to 33.83°C, scenario 2 to 33.82°C and scenario 3 to 33.39°C. However, taking into account the energy consumption, scenario 1 has the lowest daily consumption but the highest average temperature, scenario 2 has almost the same temperature but higher energy consumption and, finally, the hybrid scenario (#3) yields the best average temperature and lower consumption compared to the normal average daily consumption but not the lowest among the three scenarios tested (see Figure 6). However, the engineer chose to apply the hybrid scenario in the real-world as he advocated in favor of achieving the best possible temperature in the plant at the cost of a slight increase in energy consumption.

5 CONCLUSIONS

The paper proposed a framework which utilizes a dedicated semantic enrichment mechanism that uses data blueprints to facilitate interaction with DLs, offering at the same time DT capabilities. The framework is able to tackle successfully the complexity present in real-time storing of high-frequency data and offers data-driven user interaction to support simulations and decision making.

Without requiring extensive technical knowledge, the framework assists users to efficiently locate and retrieve information from large data sets and convert raw data into meaningful data. The proposed approach is divided into a series of steps with which organizations can enhance data processing and analysis and be able to study the effects of possible actions in a controlled, simulated environment.

The applicability of the framework was demonstrated using a real-world case-study conducted in a poultry meat factory. Three scenarios were created and tested regarding the control of temperature in breeding farms using automatic ventilation systems that open windows and/or start the operation of large ceiling fans. The scenarios were evaluated in terms of successfully controlling the current inside temperature and keeping energy consumption at acceptable levels. The stakeholders-engineers of the factory were quite satisfied and highly appreciated the support they received during simulations as they were able to differentiate between the optimal case they would like to apply in reality.

Future work will focus on three axes: The first is to explore further functional aspects of the DT offering better services and more graphical tools and visual representations of the data. The second is to extend the interaction with users by enhancing the visual querying part of the dashboard developed via game engines, such as Unreal and Unity, and providing a more gamified experience which will further ease the processing and analysis of the data. Finally, the third axis will revolve around exploring different forms of DLs and data formats to investigate how different sources of data and formats affect the applicability of the proposed approach.

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