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Guerra, Victor; Hamon, Benoit; Bataillou, Benoit; Inamdar, Adwait; van Driel, Willem D.

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Towards a digital twin architecture for the lighting industry

Victor Guerra [a,*], Benoit Hamon [a], Benoit Bataillou [a], Adwait Inamdar [b], Willem D. van Driel [b,c]

[a] Pi Lighting Sarl, Avenue Ritz 19, Sion, 1950, Switzerland
[b] Delft University of Technology, Mekelweg 5, Delft, 2628 CD, The Netherlands
[c] Signify, High Tech Campus 7, Eindhoven, 5656 AE, The Netherlands

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ABSTRACT

This paper introduces an ontology-based Digital Twin (DT) architecture for the lighting industry, integrating simulation models, data analytics, and visualization to represent luminaires. The ontology standardizes luminaire components, facilitating interoperability with design tools. The calculated ontology-level metrics suggest mid-level complexity with Size Of Vocabulary (SOV) at 37, Edge-to-Node Ratio (ENR) at 0.865, Tree Impurity (TIP) at 0, and Entropy Of Graph (EOG) at 2.61. A use case explores the utility of the ontology in the design phase across two different geographical locations, assessing environmental adaptability. The ontology captures opto-thermo-electric interactions, providing insights into luminaire performance. Results from inflating the DT and conducting simulations align with existing literature, indicating a degradation of around 12% over 8 years on the radiant flux. This ontology, up to the authors' knowledge, is the first formal definition for the lighting industry, aiming to encompass the entire luminaire lifecycle. The current focus is on design and operational phases, with potential future enhancements to include real-time monitoring for performance evaluation and predictive maintenance. This work contributes to luminaire analysis and supports the development of sustainable lighting solutions in the industry.

1. Introduction

The term Digital Twin (DT) has become a commonly used phrase in the context of products, processes, businesses, and more during the last years. Nevertheless, the concept was first introduced in 2003 by Grieves [1], but the term was first defined in NASA's Technology Roadmap in 2010 (revised in 2012) [2] and was greatly expanded in [3]. Thus, the concept primarily evolved in the context of aerospace and manufacturing applications and was later embraced by many other industries such as healthcare, automotive and, during recent years, lighting as well.

The emergence of DTs within the lighting industry presents a transformative approach to address the challenges of optimizing energy usage, maintaining control, and improving overall system performance. Integrating virtual replicas with physical lighting systems, DT architectures leverage advanced technologies like the Internet of Things (IoT), cloud computing, and data analytics to enable real-time monitoring, analysis, and simulation of lighting systems.

A DT is a virtual representation of a physical object, process, or system, encompassing the digital counterpart of its real-world counterpart [4]. It captures the properties, behavior, and characteristics of the physical entity in real time, facilitating data exchange and interaction between the virtual and physical components. Consisting of three fundamental components [5]—the physical entity, the virtual model, and the connection enabling data exchange—DTs serve a general purpose of providing valuable insights, enabling predictive analysis, facilitating optimization, and supporting decision-making throughout the life cycle of the physical object or system. This is depicted in Fig. 1.

Within the context of the lighting industry, DT architectures hold immense potential for revolutionizing the way lighting systems are designed, operated, and managed. By generating virtual replicas of lighting assets such as indoor lighting fixtures, smart light bulbs, street lighting, horticulture lighting, or vehicular lighting, DT architectures enable real-time monitoring, analysis, and optimization of the entire lighting ecosystem. This technology allows for the visualization and simulation of various lighting scenarios, facilitating the assessment of energy consumption and identification of areas for improvement.

One of the key advantages of DT architectures in the lighting industry is their ability to integrate data from multiple sources, such as meteorological stations or weather forecasting services. By incorporating this information, DTs enable advanced lighting control strategies that consider environmental factors in real time, resulting in enhanced energy efficiency and improved user comfort. Moreover, DT architectures

* Corresponding author.
E-mail address: victor.guerra@pi-lighting.com (V. Guerra).

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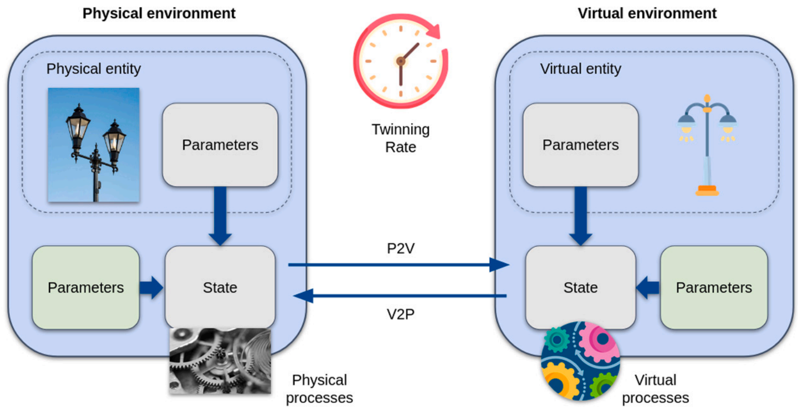

Fig. 1. DT concept applied to the lighting industry. The entities (both physical and virtual) are defined by a set of parameters or variables, that along with the environmental parameters conform the state. The synchronization or twinning between the physical and virtual entities may occur in both directions, conforming the physical-to-virtual (P2V) and the virtual-to-physical (V2P) pathways. Physical entities are subject to physical processes such as degradation, whilst virtual processes can be applied in the digital domain to perform simulations or optimizations.

facilitate predictive maintenance, empowering stakeholders to proactively identify faulty components and optimize maintenance schedules. This helps minimize downtime, extend the lifespan of lighting assets, and reduce maintenance costs.

The adoption of DT architectures in the lighting industry also enables stakeholders to conduct virtual simulations and scenario testing. By evaluating the impact of design changes, lighting strategies, and the integration of new technologies before implementation, stakeholders can reduce the risks associated with system modifications and make informed decisions [6]. This approach fosters optimization, improves performance, and ensures that lighting systems align with the evolving demands and challenges of the modern world.

In addition, DTs provide valuable operational insights into energy consumption patterns, performance metrics, and inefficiencies. Leveraging advanced technologies like IoT and data analytics, DTs enable the users to identify energy-saving opportunities, optimize lighting schedules, and dynamically adjust parameters (mainly driving current) to achieve optimal energy efficiency without compromising performance. Moreover, DTs facilitate predictive analytics, allowing the operators to anticipate maintenance needs and optimize the lifespan of lighting assets. By continuously monitoring and analyzing data, DTs empower stakeholders to make informed decisions, reduce downtime, and minimize operational costs. This paper is framed within the context of the AI-TWILIGHT project [7], which seeks to transform the European lighting industry by integrating DTs and Artificial Intelligence (AI). The project addresses the need for enhanced warranty, customization, and the integration of electronics and sensors in lighting systems. AI-TWILIGHT aims to overcome the limitations in the current lighting industry by combining DTs with AI for product design, efficient and scalable operation, and performance prediction. The project's objectives include creating DTs, developing self-learning models, and applying these in real-world scenarios. This work contributes to AI-TWILIGHT by developing a DT architecture for the lighting industry, focusing on an effective ontology and topology, and analyzing its potential applications and impact.

The introduction of an ontology-based DT architecture in the lighting industry represents a novel contribution to the field, addressing the specific requirements of lighting system optimization at different levels (from design to operation). This research introduces a formalized DT framework specifically tailored for the target industry, diverging from the traditional application domains of DTs. The proposed architecture leverages IoT, cloud computing, and data analytics to enable real-time synchronization between virtual models and physical systems. It facilitates enhanced operational control, energy efficiency, and predictive maintenance. The framework's key added value lies in its ontological approach, which provides a structured methodology for data integration and system representation, essential for accurate monitoring and scenario testing and optimization. This work presents this architecture as an adaptable and scalable model, suggesting its potential to be incorporated into current design flows and applications, fostering data-driven decision-making in the lighting industry.

The rest of the paper is organized as follows: Section 2 provides a state-of-the-art analysis on DTs in various industries, revealing research gaps in the application of this technology to lighting. Section 3 explores the challenges faced by the industry whilst Section 4 focuses on luminaire modeling. In Section 5, the proposed DT architecture is presented, detailing the ontology, topology, and connectivity requirements. Section 6 describes an example use case, demonstrating a practical application and some simulation results. Finally, Section 7 concludes the paper by summarizing the key findings, discussing limitations, and ongoing efforts to address them.

2. Related work

This section provides a comprehensive overview of the existing research, standards, and industry use cases related to DT technology. The objectives of this section are twofold: first, to present a thorough understanding of the current state of DT technology and its applications across various domains, and second, to identify the gaps, challenges, and emerging trends in the field.

2.1. Relevant standards to digital twins

The DT ecosystem is a rapidly evolving field that is increasingly being recognized for its potential to revolutionize various industries. As with any emerging technology, the establishment of robust and comprehensive standards is crucial to ensure interoperability, reliability, and effectiveness of DT implementations. Several prominent standard developing organizations, including the International Organization for Standardization (ISO), the International Electrotechnical Commission (IEC), the International Telecommunication Union (ITU), and the Institute of Electrical and Electronics Engineers Standards Association (IEEE-SA), IPC – Association Connecting Electronics Industries (formerly, Institute for Printed Circuits) have been actively working on the standardization of DT technologies.

Tao et al. introduced in [8] a five-dimensional model of a DT ecosystem, which has following key components: physical entities, virtual entities, data, connection, and services. Each of these components presents unique challenges and requirements that need to be addressed by the standards.

- **Physical Entities**. Standards, such as IEEE 1451, are crucial in a DT system as they define the boundaries, functionalities, and data collection mechanisms for physical entities. IEEE 1451, a set of smart transducer interface standards, ensures compatibility and seamless integration of data from diverse sensors, facilitating the interpretation and utilization of sensor data in the DT system.
- **Virtual Entities**. Virtual entities, the digital counterparts of physical entities, require standards that define their structure and modeling. The IEC 63278-1 ED1-Asset administration shell (AAS) and IEEE P2806 standards define the structure and modeling of virtual entities in DT systems. The AAS standard provides a semantic model for describing asset characteristics, while the IEEE P2806 standard focuses on high-speed protocol conversion and unified data modeling. Moreover, the IPC 2551 standard establishes properties, types, complexities, and readiness levels for DTs, covering product definition, manufacturing information, and lifecycle information.
- **Data**. The DT ecosystem is inherently data-driven, making the standardization of data structures and properties a critical aspect. Standards should facilitate data exchange between different DT systems and ensure interoperability. The ITU-T Y.4473 standard, which specifies an application programming interface (API) for managing and retrieving observations and metadata from heterogeneous IoT sensor systems, is a key standard in this regard. It enables the integration and management of diverse IoT devices and data sources in a DT system. Additionally, the ISO/IEC Guide-77 provides general advice and guidance for the description of products and their characteristics, which can be crucial for standardizing the way data is represented and exchanged in a DT system.
- **Connection** Standards for connection in the DT ecosystem should address the communication and interoperability requirements to enable interconnection between entities. The IEEE 2888.3 standard facilitates interactions between physical and digital objects, enabling integration and access control. It ensures seamless communication and asset management in a DT. The ISO/TR 18161 standard focuses on data exchange and interoperability among sensor-equipped physical products. It sets requirements for smart systems and cyber–physical communications, ensuring effective data exchange in DT environments.
- **Services**. Standards for services in the DT ecosystem should define the services provided by DTs and ensure their quality and reliability. The ITU-T E.800 recommendation, which defines Quality of Service (QoS) as the collective effect of service performance, which determines the degree of satisfaction of a user of the service, is a crucial standard in this regard. It provides a set of commonly used terms in the study and management of QoS, which is crucial for ensuring the reliability and effectiveness of services provided by DTs.

There are some applications that have pioneered the development of DT standards, such as the manufacturing, healthcare, and smart cities industries.

The manufacturing industry is one of the earliest adopters of DT technology, leveraging it for process optimization, predictive maintenance, and product lifecycle management. Key standards in this domain include the ISO 23247 series, which provides guidelines for implementing DTs in smart manufacturing. This series covers aspects like the digital representation of manufacturing elements, data exchange, and dynamic scheduling of manufacturing tasks. Another significant standard is the IEC 62832 series, which defines a digital factory framework for manufacturing systems, providing guidelines for data management and system modeling. The IEEE P2806 standard also plays a crucial role in this industry by defining high-speed protocol conversion, unified data modeling, and data access interfaces for heterogeneous data situations in the DT.

Furthermore, in the healthcare industry, DTs are used for patient monitoring, personalized treatment planning, and medical training. Standards in this domain need to address unique challenges related to patient privacy, data security, and interoperability of health information systems. The Health Level Seven International (HL7) standards, particularly the Fast Healthcare Interoperability Resources (FHIR), provide guidelines for the exchange, integration, sharing, and retrieval of electronic health information. These standards ensure that patient data can be seamlessly integrated into DTs while maintaining strict privacy and security controls.

Finally, DTs in smart cities are used for urban planning, infrastructure management, and environmental monitoring. The ITU-T Y series of recommendations provide guidelines for the implementation of DTs in smart cities. For instance, the ITU-T Y.4469 recommendation defines the framework and capabilities of a DT-based smart city, including aspects like data collection, data analysis, and service provision. The ITU-T Y.DTN-ReqArch standard is also crucial in this domain, specifying network resource management for analyzing, diagnosing, simulating, and controlling the physical network based on the network DT.

While significant progress has been made in the standardization of DT technologies, there are still some gaps to address. The dynamic and complex nature of the DT ecosystem needs a continuous and collaborative effort from the standardization bodies and the DT community to develop robust and comprehensive standards that can keep pace with the rapid advancements in DT technologies. The standards mentioned, among others, provide the foundational building blocks for the development and implementation of DTs, ensuring interoperability, reliability, and effectiveness of these systems. As the DT ecosystem continues to evolve, it is imperative that these standards are continuously reviewed and updated to reflect the changing landscape and requirements of DT implementations. This will ensure that the full potential of DTs can be realized across various industries, driving innovation and efficiency in a wide range of applications.

2.2. Brief literature review

2.2.1. Adoption across industries

In the manufacturing industry, DTs are used for production planning and design, maintenance, product lifecycle management, manufacturing, layout planning, and process design [9]. On the other hand, in the energy sector, DTs are used to forecast the life expectancy of wind turbines [10]. Moreover, in the healthcare domain, DTs have been implemented to increase the accuracy, recall, and F1 score of stem cell detections [11]. In the agricultural industry, DTs have been used for energy consumption analysis, system failure analysis and prediction, real-time monitoring, optimization/update, and as a technology integration tool [12]. Even in the dental industry, DTs have been explored for their potential value in remote learning, providing a dynamic virtual representation of physical objects or systems for understanding, learning, and reasoning [13].

In the lighting industry, specifically in the context of LED technology, DTs can be leveraged to enable real-time system performance assessment and improve Prognostics and Health Management (PHM) [14]. The DTs can simulate the behavior and conditions of products and systems through mathematical models and data. Machine learning algorithms and artificial intelligence are often employed to analyze system operation models and identify correlations among data generated in *in situ* and in-field (deployment) operation, as well as the lifetime assessment of LED products and systems.

2.2.2. Modeling approaches and workflow

Building a DT usually involves several methodologies, each with its unique approach and benefits. The process typically begins with the creation of a virtual model that mirrors a physical object or system.

This model is then populated with data gathered from sensors attached to the physical counterpart, creating a dynamic and data-driven replica [15].

One common methodology is physics-based modeling, where the DT is built based on the physical laws governing the behavior of the real-world system. This approach is particularly useful when dealing with systems where the underlying physics are well-understood, such as mechanical or electrical systems [16]. Another approach is data-driven modeling, which leverages machine learning algorithms to create the DT. This method is particularly useful when the system is too complex to be described by simple physical laws, or when the system behavior is influenced by many variables that interact in non-linear ways. Machine learning algorithms can identify patterns and correlations in the data, which can then be used to predict future behavior [17]. In addition, hybrid models combine elements of both physics-based and data-driven approaches. These models use physical laws to describe parts of the system where the physics are well-understood, and machine learning algorithms (also known as physics-informed networks) to model the parts of the system that are too complex or poorly understood [18,19].

These methodologies are usually formalized employing a semantic representation of the physical entities. Some standards already consider this approach, and it is deeply adopted by the manufacturing industry [20].

2.2.3. Applications in the lighting industry

The possibility of improving energy efficiency is one of the claims of DTs for the lighting industry. In [21], a DT combining lighting and surveillance systems for improved energy efficiency was proposed. The system incorporated a dynamic Building Information Modeling (BIM) platform, real-time video stream pre-processing, and a cloud database for data fusion. The authors validated the system's effectiveness over a two-week period, achieving an accuracy of up to 95% in smart decision control and reducing energy costs by approximately 79%. Notably, the integration of a dynamic mission profile for the luminaires based on real-time lighting needs enhanced the system's capabilities.

A similar approach to Tan et al.'s work [21] was conducted by Seo and Yin in [22]. In their work, the authors integrated a DT-enabled lighting system in a university in Daegu, South Korea. The main objective of the DT was reducing the energy consumption of the installation using InfraRed (IR) presence and illuminance level sensors as inputs in combination with the lectures schedule. This approach achieved around 60% energy savings with respect to the previous human-supervised lighting, which implied an average of 10.7 h daily wasted lighting (luminaires turned on in the absence of occupants).

Predictive maintenance is also other important claim of DTs, which is a natural corollary of the adoption of the technology. Ibrahim et al. analyzed in-depth most of the data-driven alternatives for performing predictive maintenance in [14]. The authors highlighted that usually, pure Physics of Failure (PoF)-based models or pure data-driven approaches are not feasible due to the lack of information about the manufacturing processes and experimental data. However, fusion prognostics (merging the previous two approaches) enables the effective use of information in order to perform Remaining Useful Lifetime (RUL) prediction.

DTs have been also applied to human-centric lighting solutions. Recently, Papatsimpa and Linnartz tried a DT-based lighting system which optimized daily light exposure in a population of 15 elder participants (who wore a sleep cycle and light intensity measurement system) [23]. The system uniquely controlled the lighting level and schedule, and did not take into account that the illumination spectrum has a direct impact on the α-opic retinal response [24]. However, despite no information is provided on the type of luminaires and their respective spectra, the results suggested that this kind of DT-enabled application may help on aligning the sleep cycles to the daily activity.

While the aforementioned works demonstrate the application of DTs in the lighting industry, they do not provide a formalized, industry-wide DT methodology. The DT in [21] is specialized for energy efficiency with a dynamic BIM, not a generalizable DT architecture. Seo and Yin's [22] study is tailored to an educational setting, focusing on energy savings rather than a comprehensive DT design. Ibrahim et al. [14] discuss predictive maintenance strategies without establishing a DT framework. Lastly, the DT-based lighting system by Papatsimpa and Linnartz [23] targets human-centric lighting for sleep cycle alignment, lacking a formal DT construction approach for diverse lighting applications. Thus, these studies, while valuable, do not offer a standardized DT construction methodology applicable across the lighting industry. Some efforts in this regard were made by Martin et al. in [25] and van der Schans et al. in [26]. Nonetheless, these works did not provide a comprehensive framework capable of supporting the heterogeneity of the industry and the interactions between the agents involved in the lifecycle of a luminaire. This work is oriented to fill that gap with a formal definition based on an ontology.

3. Challenges and opportunities in the lighting industry

Currently, the lighting industry is facing several key challenges in terms of efficiency, sustainability, and maintenance. These challenges include:

- **Energy Efficiency**. The lighting industry aims to reduce energy usage, but traditional systems often lack efficient controls, leading to excess consumption, higher costs, and increased carbon emissions.
- **Sustainability**. The lighting industry is challenged to adopt sustainable practices, including reducing energy consumption, using eco-friendly materials, and embracing sustainable manufacturing. It also seeks to transition to renewable energy and implement circular economy principles in product design and disposal.
- **Maintenance and Lifespan**. Lighting systems need regular maintenance for optimal performance and longevity. Traditional maintenance, often based on schedules or reactive approaches, can be inefficient. Proactive strategies that predict and address issues before failures occur can reduce downtime and extend asset lifespan.
- **Technological Advancements**. The lighting industry faces the challenge of adapting to trends like smart lighting, IoT connectivity, and data analytics. Effectively implementing these technologies demands expertise, resources, and adaptation to evolving standards.
- **Regulatory Compliance**. Lighting industry players face the challenge of complying with evolving regulations and standards related to energy efficiency, safety, and environmental impact, adding complexity to their operations.

Addressing these challenges requires innovative solutions and original approaches. The adoption of DT technology, as it was aforementioned, may help improve all these aspects and provide a long-term solution for complex current and future lighting systems. Based on the listed challenges, DTs present several opportunities for the lighting industry, which include:

- **Energy Optimization**. DTs facilitate real-time monitoring of lighting systems, offering insights for energy optimization. They can leverage sensor data to adjust illumination and identify energy-saving opportunities, leading to enhanced efficiency and cost savings.
- **Predictive Maintenance**. Traditional lighting maintenance, often based on scheduled or reactive approaches, can be inefficient. DTs enable predictive maintenance by analyzing real-time sensor data within the DT framework to detect early faults. This approach optimizes maintenance schedules, reduces downtime, and extends asset life, essential for large-scale deployments like cities or buildings.

- **Design and Simulation**. The adoption of DTs enables designers to assess design alternatives and impacts on light distribution, color rendering, and energy consumption, while also facilitating complex simulations that integrate feedback from various stakeholders, enhancing collaborative decision-making and system optimization.
- **Data-Driven Decision-Making**. DTs generate information that can be leveraged for data-driven decision-making. By integrating data from various sources, such as occupancy sensors, weather forecasts, and energy consumption data, DTs can provide insights for optimizing lighting systems.
- **Sustainable Practices**. DTs enhance the lighting industry's sustainability by analyzing real-time data for energy-efficient solutions and sustainable manufacturing, thus reducing environmental impact. They aid in end-of-life management and product circularity, enabling efficient recycling and resource recovery, thereby minimizing waste and environmental footprint.
- **Enhanced Customer Experience**. DTs enhance customer experience by providing personalized lighting solutions that adjust to user preferences, behavior, or even medical needs, creating comfortable environments and supporting the development of tailored smart lighting systems with a human-centric perspective.

Adopting DT technology can revolutionize the life cycle of lighting systems, from production to operation, accelerating optimized designs' market introduction and enabling predictive maintenance for cost reduction and sustainability. However, a readily implementable commercial DT architecture is yet unavailable. For widespread DT adoption, efficient LED device characterization methods and a simple DT architecture are necessary, benefiting the entire lighting ecosystem [27]. This work primarily discusses the architecture, with the next section introducing luminaire modeling as a foundational DT component.

4. Multi-physical luminaire modeling

The luminaire is the baseline physical entity to be virtually replicated in the DT architecture. It usually consists of five elements as shown in Fig. 2:

- **LED device**. LEDs are compact, energy-efficient semiconductor devices that emit light of a specific spectrum when electrically powered. In a luminaire, multiple LEDs are used in an array to reach an objective radiant power or to produce a specific color. This collaborative usage allows for a wide variety of colors and levels of illumination, satisfying diverse lighting requirements.
- **Printed Circuit Board (PCB)**. The PCB is a platform that connects and controls the luminaire's electrical components. It provides mechanical support and electrical pathways, including conductive tracks and pads, for components like LED devices and drivers. The PCB design is crucial for ensuring proper electrical connectivity, heat dissipation, and efficient luminaire operation.
- **Secondary optics**. Secondary optics, including lenses, reflectors, and diffusers, are used to shape and guide the light emitted from LED devices, ensuring the desired lighting distribution and control. These components optimize light intensity, beam angle, and distribution pattern, enhancing efficiency, reducing glare, and improving visual comfort by directing light to where it is most needed.
- **Driver**. The driver manages electrical power for the LED devices. It adapts the incoming current into the appropriate voltage and direct current necessary for LED operation. Providing stable power, the driver shields LEDs from voltage changes and offers dimming or control options. It includes protection mechanisms like overcurrent and overtemperature safeguards for the luminaire's safe and reliable operation.

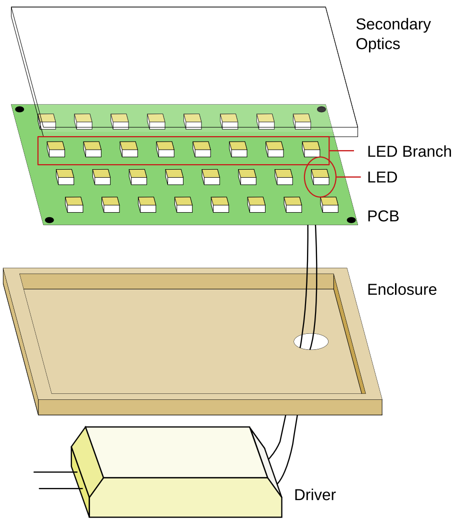

Fig. 2. Elements comprising a typical luminaire.

- **Enclosure**. The enclosure, or luminaire housing, is the outer shell providing protection, support, and aesthetics to the luminaire. It encapsulates all internal components, including LEDs, PCB, driver, and secondary optics. The enclosure is built to resist environmental factors like dust, moisture, and temperature changes while ensuring efficient heat dissipation. Additionally, its design facilitates mounting, aiming, and adjustments for easy installation and maintenance.

Modeling accurately these elements and their relationship is required for generating a DT with an acceptable fidelity. The following subsections provide more insight about LED, PCB, driver, and secondary optics modeling in the frame of a DT for the lighting industry. These elements are usually affected by several factors in a nonlinear manner, and in addition, their performance is affected by the accumulated stress (aging).

4.1. LED device modeling

LED operation mainly depends on the pn-junction temperature (T_j) and the driving current (I_f), which are abbreviated as the operation point. These two factors determine the forward voltage drop (V_f) on the device, its output radiant flux (Φ_{opt}), and its spectrum ($S(\lambda)$). During Delphi4LED project [28], specific multi-domain full characterization processes (relating the optical, thermal, and electrical domains) to obtain robust closed-form equations for these variables were successfully defined [29]. Nonetheless, the procedures were time consuming and they have been revisited during project AI-TWILIGHT [27], speeding up them to increase the likelihood of LED manufacturers about including this data on their data sheets [30].

The following formulae present these relations for V_f (Eq. (1)) and Φ_{opt} (Eq. (2)) [29]:

$$V_f(I_f,T_j) = I_f \cdot R_s + mV_t \ln\left(1+\frac{I_f}{I_0}\right) + (T_j - T_{ref})\Delta V(I_f,T_j)$$

$$\Delta V(I_f,T_j) = \begin{pmatrix} 1 \\ T_j + T_{ref} \end{pmatrix}^T \begin{pmatrix} \theta_1 & \theta_2 & \theta_3 \\ \theta_4 & \theta_5 & \theta_6 \end{pmatrix} \begin{pmatrix} 1 \\ I_f \\ I_f^2 \end{pmatrix} \quad (1)$$

$$\Phi_{opt}(I_f,T_j) = I_f \cdot \begin{pmatrix} \ln^2 I_f \\ \ln I_f \\ 1 \end{pmatrix}^T \begin{pmatrix} a_A & b_A & c_A \\ a_B & b_B & c_B \\ a_C & b_C & c_C \end{pmatrix} \begin{pmatrix} T_j^2 \\ T_j \\ 1 \end{pmatrix} \quad (2)$$

R_s is the series resistance of the LED package, m is its ideality factor, V_t is the thermal voltage, T_{ref} is a reference temperature used to fit the model, θ_i are fitting coefficients, and ΔV is a temperature-dependent voltage drop. a_i are the fitting coefficients for the radiant flux model.

LED spectrum modeling is an open research field in which the output spectrum $S(\lambda)$ is predicted by the operation point (I_f, T_j). For monochromatic LED devices, changes in the operation point can shift the peak wavelength and intensity of the emitted light, resulting in variations in the LED spectrum.

Phosphor-converted LEDs, which blend a blue or ultraviolet LED with a phosphor coating, introduce additional variables. The phosphor material's characteristics, like absorption and emission spectra, concentration, and thickness on the LED surface, influence the resulting spectrum. The phosphor's excitation efficiency under various LED operating conditions also impacts conversion efficiency and the spectrum. Benkner et al. found that the Split Pearson VII model functions provide more accurate results than traditional Gaussian-based models for both monochromatic and phosphor-converted sources [31]. Therefore, the LED spectrum can be modeled as shown in Eq. (3).

$$S(\lambda, I_f, T_j) = \sum_{i=0}^{n_f-1} a_i \tilde{S}_{sPVII}\left(\lambda - \lambda_i, \sigma_i, s_i, m_i\right) \tag{3}$$

a_i is a weighing coefficient, $\tilde{S}_{sPVII}(\cdot)$ is the energy-normalized Split Pearson VII function, λ_i is the offset of the ith component, σ_i is the scale parameter, and s_i and m_i are the shape parameters. All these parameters depend on the operation point.

LED variability due to manufacturing processes and inherent differences in characteristics must be considered in luminaire modeling. Factors like material properties and production variations affect LED performance, but their impact is averaged as the number of LEDs in the luminaire increase. Accounting for this variability is crucial for accurate luminaire performance predictions.

Moreover, considering aging is vital in LED device modeling as it impacts performance and longevity. Industry standards like LM-80 and TM-21 [32] help assess aging and estimate LEDs' RUL. LM-80 standardizes the measurement of LEDs' lumen maintenance over a specific period, generally between 6,000 and 8,000 h. On the other hand, TM-21 uses this data to extrapolate the long-term performance of LEDs. Applying these standards allows manufacturers and designers to make informed decisions about LED devices' expected lifetime and reliability in luminaires. Accurate RUL estimates enable proactive maintenance planning and consistent performance throughout the product's lifetime.

Nonetheless, including the aging process in the LED model is not trivial since the typical characterization methods assume constant stress conditions that significantly differ from real-world operation. In addition, the mission profile of a device and its operation point over time define the likelihood of different failure modes (e.g., at solder level, at package level, at die level). In general terms, aging is a cumulative process which may be considered memory-less under certain assumptions, allowing the application of Miner's rule [33]. For simplicity and from a DT viewpoint, Eqs. (1) and (2) can be multiplied by a scalar function in which cumulative stress is introduced (Eqs. (4) and (5)). On the other hand, stress can be introduced into Eq. (3) by means of a shape-modifying function as it shows Eq. (6).

$$V_f(I_f, T_j, C) = \mathfrak{V}(C) \cdot V_f(I_f, T_j) \tag{4}$$

$$\Phi_{opt}(I_f, T_j, C) = \mathfrak{P}(C) \cdot \Phi_{opt}(I_f, T_j) \tag{5}$$

$$S(\lambda, I_f, T_j, C) = \mathfrak{S}(\lambda, C) \cdot S(\lambda, I_f, T_j) \tag{6}$$

C is a cumulative stress metric following Miner's rule which is bounded in the $(0, 1)$ interval. $\mathfrak{V}(C)$ and $\mathfrak{P}(C)$ are scalar functions that model the change on forward voltage and radiant flux due to cumulative stress. Finally, $\mathfrak{S}(\lambda, C)$ is a unitary-integral function that captures the change on the LED spectrum shape due to stress.

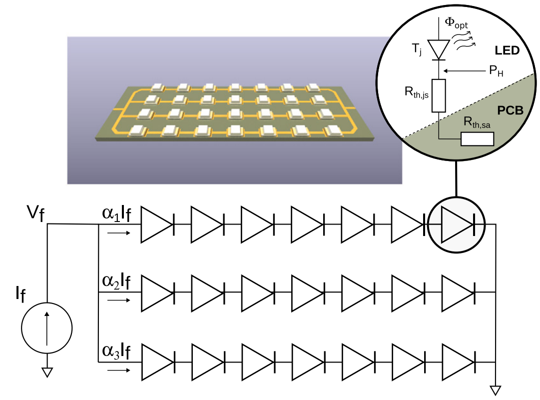

Fig. 3. Example arrangement of LED devices on a PCB.

4.2. PCB modeling

PCB modeling is key to comprehending a luminaire's electrical and thermal behavior. It captures LED-PCB interactions, enhancing performance and reliability in the DT. Research and industry practices stress the importance of PCB modeling for efficient heat dissipation, component stress reduction, and system longevity [34]. The luminaire's LED devices, often arranged in an array (Fig. 3), influence the electrical behavior, particularly voltage distribution. Accurate voltage estimation for each device requires considering the electrical connections between LEDs and the impact of current flow on performance, reliability, and junction temperature.

The heating of LED devices has a significant impact on the overall thermal behavior of the PCB. To estimate the temperature of each LED device accurately, it is crucial to consider the thermal interactions within the system. Standards such as LM-80 and TM-21 provide guidelines for LED aging and the estimation of the remaining useful lifetime based on temperature profiles. Furthermore, the design of the luminaire should account for the potential for crosstalk between LED devices, as this can influence the thermal performance and reliability of the PCB.

To model the electrical and thermal behavior of the PCB, a resistor network analysis is commonly employed. This simple yet effective approach involves constructing a network of resistors that represents the electrical connections and thermal pathways within the luminaire. By solving the network equations, it is possible to determine the thermal flow on the PCB and eventually the voltage across the LED devices by solving the electro-thermally coupled equations. Eq. (7) illustrates the concept, complementing Fig. 3.

$$\begin{pmatrix} T_{j,1} \\ T_{j,2} \\ \vdots \\ T_{j,n} \end{pmatrix} = T_p + \begin{pmatrix} R_{th,1p} & R_{th,12} & \cdots & R_{th,1n} \\ R_{th,21} & R_{th,2p} & \cdots & R_{th,2n} \\ \vdots & \vdots & \ddots & \vdots \\ R_{th,n1} & R_{th,n2} & \cdots & R_{th,np} \end{pmatrix} \begin{pmatrix} P_{H,1} \\ P_{H,2} \\ \vdots \\ P_{H,n} \end{pmatrix} \tag{7}$$

The diagonal terms of the resistor network matrix $R_{th,ip}$ correspond to the thermal resistance between the junction of the ith LED device and the PCB reference temperature T_p, whilst the other terms $R_{th,ij}$ are associated to thermal crosstalk. It must be noted that the heating power of each LED $P_{H,i}$ can be extracted from Eqs. (1) and (2) applying the conservation of energy as Eq. (8) describes (the same applies for the aging-enabled version of the equations).

$$P_H(I_f, T_j) = V_f(I_f, T_j) \cdot I_f - \Phi_{opt}(I_f, T_j) \tag{8}$$

It is straightforward to notice the strong coupling between the sets of thermal and electrical equations. Numerical methods are needed to solve the equations, which should account for the electrical arrangement of the LEDs. Additionally, the estimated temperatures of the LED devices offer valuable information regarding thermal management and the potential for degradation. Finally, Eq. (9) describes the voltage balance between LED branches and how current is split between them according to the thermally-dependent forward voltage drops.

$$\sum_i V_{f,i}^{(k)}\left(\alpha_k I_f, T_{j,i}^{(l)}\right) = V_{driver} \quad /\forall k \tag{9}$$

Where i is the index of the ith LED on a given branch, denoted by k. V_{driver} is the output voltage of the LED driver, determined by the equivalent impedance of the LED array. α_k is the portion of current diverted to the kth branch, with the constraint $\sum \alpha_k = 1$.

4.3. Secondary optics modeling

Modeling secondary optics in the proposed DT involves considering the effects on output radiant flux and spectrum, material robustness against yellowing, and material aging. Aging and yellowing are driven by physical mechanisms like photodegradation, chemical reactions (oxidation and polymer degradation), and environmental factors [35]. Yellowing results from various factors such as chromophore formation, photo-oxidation, and degradation of additives or stabilizers in the materials. Understanding these mechanisms enables the DT to simulate aging and yellowing processes, aiding predictive analysis and design decisions for the long-term performance and aesthetics of the luminaire's secondary optics.

Most luminaires use polymethyl methacrylate (PMMA) or polycarbonate (PC) for secondary optics due to cost efficiency, lighter weight, and higher mechanical resistance compared to inorganic glass. The aging process of these materials significantly affects lighting system design and performance. Prolonged exposure to intense light sources leads to photo-thermal degradation of PMMA (or acrylic) and PC, and their mechanical properties also degrade under temperature, light exposure, and humidity. Regarding optical property degradation, PMMA is reportedly more reliable than PC [36,37]. PMMA materials maintain near-unchanged transmittance functions after photo-thermal degradation, while PC tends to yellow and reduce transmittance in the spectrum's bluer regions over time. However, PC offers around 15 times more mechanical resilience than PMMA.

The degradation behavior of both materials is typically modeled using Arrhenius models [38] (Eq. (10)), considering exposure to stress factors like specific wavelengths, temperature, and humidity. These materials exhibit reciprocity, with degradation rates linearly dependent on radiant flux. However, existing models primarily focus on controlled laboratory conditions rather than natural lighting environments. Moreover, temperature-induced degradation observed in thermal chambers, which uniformly heat samples, differs from field conditions where lenses may experience temperature gradients. Despite these limitations, such impact on DT fidelity is marginal compared to LED device aging.

$$-\frac{\mathrm{d}\ln \Phi(t)}{\mathrm{d}t} = AS(\lambda_r)\exp\left(-\frac{E_a}{KT}\right) \tag{10}$$

Where $-\mathrm{d}\ln\Phi(t)/\mathrm{d}t$ is the exponential decay rate of the transmitted radiant flux, A is a pre-exponential constant, E_a is the activation energy of the aging process, K is a gas constant, and T is absolute temperature. $S(\lambda_r)$ is the radiant intensity of the source at significant reference wavelength λ_r for the photo-degradation process (typically around 350 nm). This last term is similar to the degradation models used for LED reliability, but assuming pure reciprocity (linear relation between rate and intensity).

4.4. Driver modeling

In the DT architecture, the LED driver acts as the interface between virtual and physical elements, enabling real-time monitoring and optimization of system performance. Accurate modeling of the driver in the DT allows for system-level simulations and evaluation of configurations, improving energy efficiency and reliability. This includes understanding driver behavior, identifying issues, and optimizing performance for better lighting system design and management.

Commonly used models for LED drivers include the electrical equivalent circuit model, which represents the driver's electrical properties using resistors, capacitors, and inductors, and behavioral models like blocks or lookup tables that describe control mechanisms and dimming capabilities. These models enable accurate simulations of the driver within the DT, assessing its impact on overall system performance and guiding optimization strategies for energy efficiency and reliability.

Driver degradation can be modeled leveraging Miner's rule [33] and the Mean Time To Failure (MTTF) estimated at each operation point [39]. This kind of model approximates the driver's relative RUL (rRUL) based on the cumulative damage induced by its operation at different working temperatures (Eq. (11)).

$$rRUL = 1 - \sum_i \frac{t_i}{MTTF_i} \tag{11}$$

Where t_i is the burning time at the ith operation point considered in the model, and $MTTF_i$ its associated MTTF. It is assumed that the driver will fail when rRUL reaches the zero level. Besides including its degradation model, the driver will be considered as a programmable current source with sensing inputs. Nonetheless, it is important to highlight that most LED drivers allow for a very limited number of temperature-sensing inputs, and only a single voltage measurement at the output of the driver. These limitations are translated into important challenges such as the synchronization of the DT state based on a few real-world measurements.

4.5. Enclosure modeling

The enclosure's modeling primarily affects the luminaire's thermal performance, with placement environment (outdoors, indoors with ample or limited convection space) significantly influencing this. The DT may use Finite Element Method (FEM) simulations using the luminaire's Computer Aided Design (CAD) description to analyze thermal performance, forming a resistor network as indicated in Eq. (7), relative to ambient temperature. FEM simulations enable accurate predictions and synchronization between the physical and virtual, providing comprehensive insight into the luminaire's thermal behavior. This information is vital for optimizing the design, performance, reliability, efficiency, and effectiveness of the luminaire across various operating environments.

5. Digital twin architecture

A DT architecture is defined by the framework that outlines its components and their interactions. This comprises the hardware and software elements, data flow processes, and the integration mechanisms that make up the DT system. In this work, it comprises ontology, topology, and connectivity. Ontology structures the lighting system identifying the entities and their relationships, topology outlines spatial arrangements for a holistic system overview, and connectivity ensures seamless data exchange between physical and digital realms, enabling real-time system optimization.

5.1. Ontology

Using an ontology for DT descriptions brings several advantages to the lighting industry. It provides a formalized understanding of the field, enabling better interoperability and a more holistic view of the lighting system components. This approach allows for unified data exchange and analysis, facilitating seamless system integration and improved decision-making. Also, the maintenance and scalability are enhanced due to the flexible nature of the ontology, allowing it to adapt to industry changes. Ultimately, an ontology-based approach enhances the DT's performance, supporting the shift towards smarter, more sustainable, and adaptive lighting solutions.

The methodology used to define the ontology of the DT is based on the following steps:

1. **Domain identification**. The current challenges of the lighting industry highlight the necessity of a comprehensive understanding of the industry's key entities and their relationships.
2. **Knowledge gathering**. The knowledge gathering phase results in a comprehensive repository covering design, operation, and management of lighting systems, including LED specifications, driver functionalities, optics, thermal traits of enclosures, and PCB design considerations, as already detailed in Section 4..
3. **Structure conceptualization**. This step aims to identify the key entities, that will be represented in the ontology to accurately model the domain-specific concepts and their interconnections.
4. **Properties definition**. This step involves specifying the object properties and data properties that describe the relationships and attributes of the entities in the DT ontology.
5. **Relationships establishment**. This step involves defining the relationships or connections between different entities or classes within the ontology, focusing on the domain, range, and cardinality (one-to-one, one-to-many, e.g.) of the relationships.
6. **Constraints specification**. Defining constraints like cardinality rules ensures integrity and consistency, guiding entity interactions. For example, in this work, it includes specifying that a PCB must have at least one LED device.
7. **Ontology formalization**. In the formalization step, identified concepts, relationships, properties, and constraints are encoded into the ontology language, creating a machine-readable format for tools like editors and reasoners. Web Ontology Language (OWL) is used for this formalization in this work.

The description presented in this work is being validated and evaluated by experts in the frame of project AI-TWILIGHT, and will eventually be refined to a stable final version.

The lifecycle and sources of information for lighting products are crucial for creating an accurate digital representation. In this context, the data can be categorized into different types based on their relevance and purpose within the DT framework (Fig. 4).

- **Basic Attributes**. This data type includes fundamental information about the lighting system that is not directly related to its manufacturing process. It encompasses details such as product specifications, model numbers, serial numbers, and other identifying characteristics.
- **Manufacturer and Supplier Data**. Supplementary data provided by the manufacturer and supplier play a significant role in constructing a DT. This data may include vendor-specific information, models (e.g., physical, black-box, behavioral, mathematical), or any additional documentation relevant to the product. The quality of this kind of information will affect the fidelity of the DT.
- **Design Data**. Design data captures the design intents of the lighting system, encompassing aspects such as the geometric shape, structural elements, optical properties, electrical diagrams, and any specific design parameters. This data allows for a comprehensive understanding of the lighting system's form and function, and will be used by the models to perform the twinning operations (physical-to-virtual and vice versa).
- **Operational and Testing Data**. The effect of this type of data is to record details about the manufacturing and quality inspection processes of the lighting system. This data provides insights into the manufacturing techniques employed, performance characteristics, test results, and compliance with relevant standards or regulations.

By consolidating these data types into a unified packet, the DT of a lighting system can be formed. The aforementioned data groupings can be represented as parameters of each one of the elements within the DT. For instance, an LED part number, footprint, and usage data

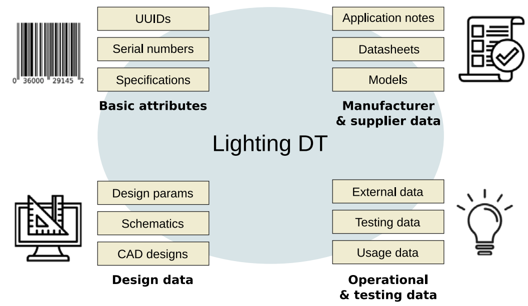

Fig. 4. Structure of the data sources used to build the DT.

would be parameters of the same element in a DT instance. It is worth noting that when multiple lighting systems are produced in the same batch or share similar characteristics, certain data entries can be generated concurrently, minimizing redundancy and optimizing data management.

Moreover, it is important to consider that not all processing and inspection data for each individual lighting component need to be included in the DT. Collaboration between manufacturers, designers, and assembly workshops can help identify the key features and inform the relevant data to be incorporated. This selective approach allows for reducing the amount of data in the DT while still providing essential information for operational and maintenance purposes.

The data flow to consider when building the lighting DT is presented in Fig. 5. Each part of the DT should have an associated model, which should be provided by the manufacturers or by specialized characterization laboratories. These models are used by luminaire designers for optimization purposes taking into account different aspects such as the mission profile, target RUL, and expected performance (e.g., color point or radiant flux). Once the design is manufactured and assembled, some quick end-of-line characterization procedures are performed. These tests output valuable information in terms of operation since they will help to reduce the uncertainty derived from the inherent intra-group variability of LED devices. Finally, once the luminaire is deployed, there will be a continuous information flow between the onboard sensors and the control station in which the luminaire's physical parameter set will synchronize with the DT using the physical-to-virtual pathway and in the opposite direction after operation optimization and control using the virtual-to-physical pathway (mainly used to configure the forward current). The current ontology focuses on design and operation, but it has been prepared to scale up in order to accommodate recycling considerations into the lifecycle definition of luminaires, aligning with Europe's Circular Economy Action Plan [40]. By incorporating materials' recyclability and design for disassembly, the evolved DT framework will promote sustainability, waste reduction, and innovation in the lighting industry. This holistic approach supports the transition to a more resource-efficient economy and drives the development of environmentally friendly lighting solutions.

In Section 4, all the parts comprising a luminaire were introduced and discussed in terms of modeling. This information, joint to the data structure (Fig. 4) and the analyzed information flow during the luminaire's lifecycle (Fig. 5) enable the formal definition of a DT ontology. Fig. 6 depicts the proposed ontology based on the aforementioned information.

Several super classes have been defined. On the one hand, Luminaire, LuminaireElement, Agent, Material, and Model classes have been defined as disjoint classes, preventing an instance to be part of them simultaneously. In addition, the Agent super class is subdivided in terms of the description presented in Fig. 5. Each agent subclass has an associated object property which defines the type of interaction with the Luminaire or LuminaireElement, named according to its role (Assemblers assemble, Simulators simulate, Designers design, etcetera). In

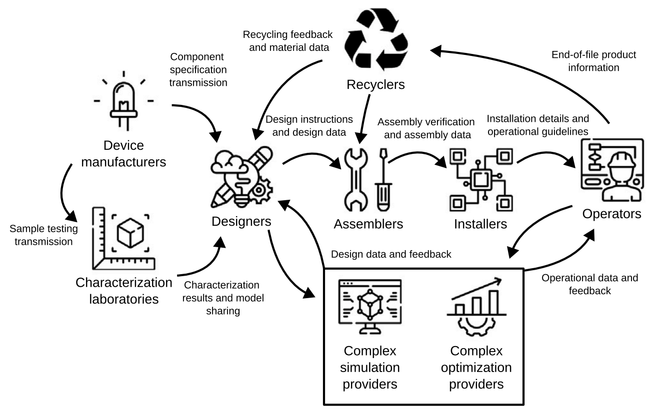

Fig. 5. Dataflow within the lighting ecosystem for creating a DT for the industry.

this case, these sibling classes are not disjoint since an Agent can be for instance, both Designer and Assembler. Despite there being agent-based ontologies such as Friend Of A Friend (FOAF) [41] or the Provenance Ontology (PROV) [42], the specific requirements of this project required the creation of a more domain-focused ontology. These pre-existing ontologies, while comprehensive and well-established in their respective fields, did not fully encapsulate the unique and specialized needs inherent to the scope of this work.

Different kinds of Models have been defined, in order to capture all the physical magnitudes presented in Section 4. Moreover, three types of Interaction have been defined: thermal, electrical, and optical. These classes are endomorphic in the LuminaireElement set, allowing interactions between any kind of element within the Luminaire. The LuminaireElement class is subdivided into classes associated to the elements comprising a Luminaire (Section 4). In addition, an LEDBranch subclass has been added to allow LED arrangements as the one presented in Fig. 3. The ontology also incorporates a ProductionBatch entity to capture essential manufacturing data, ensuring traceability and consistency. This addition aids in tracking component variations and aligns with quality control efforts. It also enriches the ontology's analytical capabilities, allowing for the correlation of performance trends and operational data with specific production batches, which is instrumental in enhancing predictive maintenance and resource planning.

The proposed ontology clearly focuses on enabling the essential aspects necessary for facilitating design and operational processes, including critical elements like simulation and optimization. Nevertheless, the ontology is structured to ensure coverage of the most pivotal components of the lighting lifecycle, laying down a robust foundation. Furthermore, it is designed with scalability as a premise, allowing for the integration of more complex relationships and entities over time. The mid-term ambition of the ontology is to provide DT capabilities from design to recycle.

Different axioms have been established to ensure the semantic consistency of the ontology. In order to show the nature of these relations, a selected subset of axioms are presented in Table 1.

With respect to the data properties, each LuminaireElement has uuid, serialNumber, or partNumber strings. The LED entities also present voltage, current, temperature, radiantFlux, and degradationMatrix values defined as double precision numbers. The output spectrum will be obtained through the SpectralModel class. The Driver class shares these properties with LED expect the radiantFlux. Furthermore, the PCB, SecondaryOptics, and Enclosure classes also have a temperature property. On the other hand, the Agent super class has Customer Relationship Management (CRM) information such as address, contact, email, etcetera. The actual role of each Agent will be reasoned according to its relation with each part of the luminaire. Finally, the Model super class determines the topology of the computations, which is explained in the following section.

Table 1
A selected subset of constraints defined to ensure the consistency of the ontology in Protege notation.

Affected class	Axiom
Enclosure	(hasMaterial some Material) and (hasThermalModel some ThermalModel)
LED	(hasOpticalModel some OpticalModel) (hasSpectralModel some SpectralModel) (hasThermalModel some ThermalModel) (hasVoltageModel some ElectricalModel)
SecOptics	hasOpticalModel some OpticalModel
MonochLED	hasSpectralModel some MonochModel
Luminaire	(hasSecOptics some SecOptics) or (hasDriver some Driver) or (hasEnclosure some Enclosure) or (hasPCB some PCB) or
PCB	hasLEDBranch some LEDBranch
LEDBranch	hasLED some LED
LED	isManufactured some Manufacturer
Manufacturer	manufactures some LED

Table 2
Comparison of ontology-level complexity metrics. The benchmark ontologies were obtained from [43].

Ontology	SOV	ENR	TIP	EOG
This work	37	0.865	0	2.61
Amino-acid	52	3.1	200	1.56
Semweb-glossary	1805	1.35	632	2.27
Parkinsons-Disease	86	0.74	0	1.86

In order to provide an idea on the proposed complexity, some ontology-level metrics have been obtained [43]. The Size of Vocabulary (SOV), related to the number of classes provides an idea of the ontology size, which is usually related to the effort needed to build and maintain it. In the case of the lighting industry, it is important to keep the SOV as small as possible to engage the stakeholders into the adoption of this paradigm. The Edge-to-Node Ratio (ENR) is the quotient between the number of relations and the class cardinality, and it measures the connectivity density of an ontology. The greater the ENR, the greater the complexity. Furthermore, the Tree impurity (TIP) indicates how far an ontology's inheritance hierarchy deviates from being a tree. It is calculated as $TIP = \#E - \#C + 1$ where $\#E$ is the subclass-type edge cardinality and $\#C$ is the class cardinality. The greater the TIP the more the ontology deviates from a pure tree structure, and hence, the more complex it is. Finally, the Entropy of Graph (EOG) is the entropy of the ontology considering the probability of each node on having i edges. Low values of EOG indicate the existence of regular structures and therefore less complexity. Table 2 presents the metrics for the proposed ontology and relates them with the values from other ontologies. Since there are no previous ontologies defined for the lighting industry (up to the authors' knowledge), this comparison serves to have an idea on the complexity of the solution in general terms and with respect to other sectors or industries. It can be observed that this work's metrics suggest that it corresponds to a mid-complexity ontology.

Using an ontology-based approach in the DT architecture promotes interoperability and data exchange by unifying different data sources, including sensors and databases. This approach results in a comprehensive representation of the lighting system and its performance. Furthermore, the ontology helps to harmonize different data formats, semantics, and standards, thus enhancing data interpretation within the DT. This facilitation of data standardization supports precise system analysis, enabling informed decision-making and system optimization. Ultimately, the utilization of an ontology in data exchange boosts the overall functionality of the DT, encouraging innovation and sustainability within the lighting industry thanks to the use of a normalized framework.

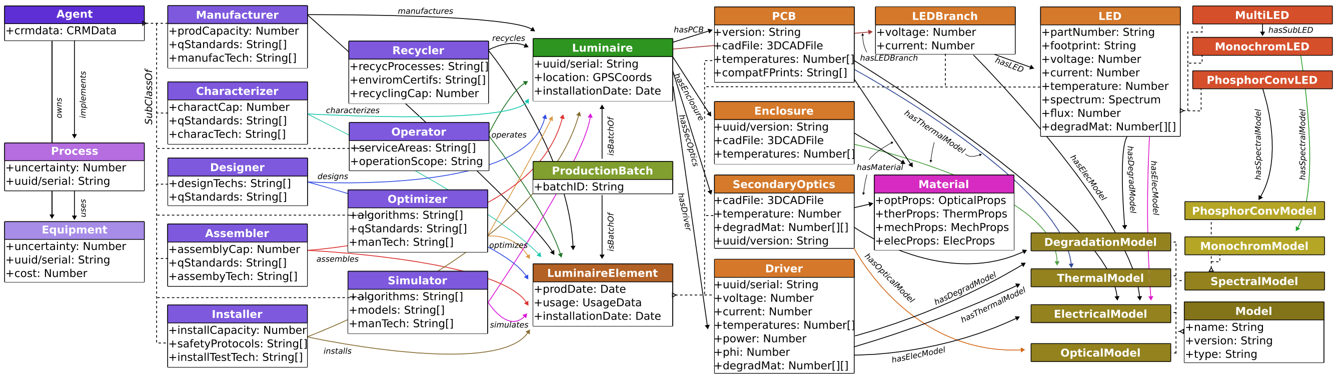

Fig. 6. Proposed DT ontology showing the main classes and their relationships as a simplified conceptual model.

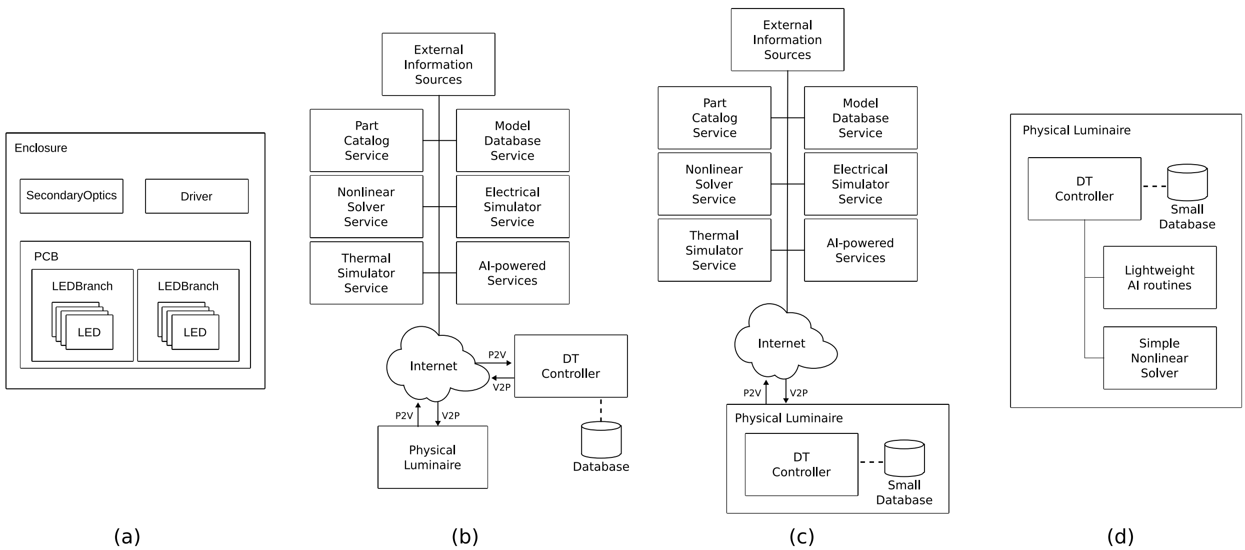

Fig. 7. Types of topology on the virtual domain of the DT. (a) Physical topology of the luminaire, (b) fully-distributed topology, (c) hybrid topology, and (d) centralized and standalone topology.

5.2. Topology

The topology is a core element of the DT architecture. It details the spatial layout and relationships between components. This topology encapsulates the real-world arrangement of LED devices, drivers, PCBs, secondary optics, etc., enabling the comprehensive analysis of the system's performance, considering heat dissipation, light distribution, and electrical connections. As shown in Fig. 1, the DT incorporates physical-to-virtual and virtual-to-physical pathways, with the physical entity's topology captured in the ontology. The virtual representation's topology, illustrated in Fig. 7, can be centralized, distributed, or hybrid. This integration of topology enhances monitoring, control, and optimization of the lighting system.

The twinning operations (P2V and V2P) are fundamental to ensure proper synchronization between the real-world object and their virtualized counterpart. Nonetheless, as it was aforementioned, there is currently a limitation on the amount of information that can be extracted *in situ*, and most of the DT state will have to be inferred from the few available measurements (typically the driver current and forward voltage, and one or two temperatures). Therefore, the twinning will have to deal with under-constrained nonlinear systems. In this situation, the physical-to-virtual pathway needs uncertainty minimization techniques considering the variability of the LED devices. This is still an open challenge which is currently being addressed assuming homogeneity on the devices.

The DT controller, which may be embedded into the physical luminaire, orchestrates the data flow between all the entities in the virtual domain. This entity also keeps track of the DT state along time, storing it into a local (or a distributed) database. One of the key advantages of the ontology defined above is that both Model and Part catalog services are enabled, providing a flexible, scalable, and updatable mechanism for all the ecosystem. The equations from Section 4 can be efficiently solved by a specialized entity (Nonlinear Solver Service), which can be fed by the thermal resistor network provided by a Thermal Simulation Service and optionally by an Electrical Simulation Service. Nonetheless, since thermal and electrical equations are strongly coupled, this last step could be included into the Nonlinear Solver Service for improved performance (avoiding latency issues due to the intensive use of API, RPC or any other communication aspect).

The incorporation of a topology definition in the DT illustrates both the physical and logical relationships among components such as lighting fixtures, sensors, and controllers. This comprehensive view shows their arrangement and inter-dependencies, reflecting the system's hierarchical or networked structure. Such structural data is vital in understanding the system behavior and performance, enabling the identification of communication pathways, control strategies, and data exchange. This enables simulation, analysis, and optimization of performance, supporting efficient operation and effective control of the lighting infrastructure through distributed, centralized, or hybrid approaches in the virtual domain.

Table 3
Impact of each protocol on the DT architecture.

Protocol	Energy consumption	Data rate	Ease of use	Scalability
Wi-Fi	High	High Beneficial for RT	Easy to set up Great compatibility	Scalable in LAN limited by coverage
Bluetooth	Low power Energy efficient	Moderate Enough for control	Easy to set up Great compatibility	Limited to PAN
ZigBee	Low power Energy efficient	Moderate Enough for control	Relatively easy	Great scalability Mesh networking Multi-hop connectivity Extended coverage
DALI	Low power overhead Also powers luminaire	Low Enough for control	Standard in the lighting industry	Moderate scalability Limited network range Limited number of devices
LoRaWAN	Low Energy efficient	Low Enough for control	Quick deployment Reduced infrastructure	Excellent scalability Large number of devices Long range
NB-IoT	Extreme energy efficiency	Low Enough for control	Easy integration Uses cellular network	Excellent scalability Large number of devices

The fusion of the ontology and the service-based architecture creates a powerful setup. This pairing utilizes the ontology's comprehensive representation and the architecture's operational capabilities. This strategy enhances flexibility, re-usability, and collaboration, enabling different stakeholders to interact with the DT through the defined services.

5.3. Connectivity

Connectivity in the DT architecture is key for communication and data exchange among system components, enabling integration between physical and digital elements. It allows real-time monitoring, control, and synchronization between the physical lighting system and its DT, with sensor data from the physical environment updating the DT in real-time. This continuous data flow facilitates anomaly detection, predictive maintenance, and optimization of energy consumption and performance.

Moreover, connectivity has a pivotal role in the architecture and facilitates bidirectional communication, enabling control signals and commands to be sent from the DT to the physical system. This interaction empowers the DT to act as a control interface, influencing the behavior of the physical lighting system in response to dynamic requirements or changing environmental conditions. For example, the DT can adjust lighting settings, modify operational parameters, or trigger automated responses based on real-time analysis and feedback.

In the lighting industry, various communication protocols and network technologies are commonly employed to establish connectivity with communications-enabled luminaires. These include Wi-Fi, Bluetooth, Zigbee, DALI (Digital Addressable Lighting Interface), LoRaWA, and NB-IoT (Narrowband IoT) among others. Each protocol or technology offers unique features and capabilities suitable for specific use cases and requirements. Table 3 summarize the impact of using each one of the mentioned protocols in terms of power consumption, data rate, ease of use, and scalability.

Outdoor luminaire connectivity typically uses DALI, LoRaWAN, or cellular networks due to their scalability, while indoor lighting commonly employs Wi-Fi, Bluetooth, or ZigBee. Despite Bluetooth's capacity for continuous data streams, it is predominantly used for user-triggered interactions rather than automated control. The data that needs synchronization between the luminaire and the designed DT is minimal, between 4 and 8 bytes per transaction, which is suitable for any of these communication technologies. The selection hinges on the specific use case, budget, and design complexity. The lighting industry's adoption of DTs could lead to more sophisticated setups, potentially expanding the information flow to a few kilobytes, including spectral information, spatially-resolved temperature probing, and LED-wise voltage measurements. In addition, due to the slow degradation rates, a constant connection is not mandatory for DTs, and the information can be synchronized on an event basis, such as lighting switching or when significant environmental changes occur. Moreover, connecting luminaires to external data sources like meteorological services may improve the DT's fidelity, particularly for outdoor lighting. In terms of costs, incorporating a DT into a luminaire is not prohibitive compared to traditional smart lighting.

6. Example use case

In this section, the DT architecture previously presented is applied to carry out the comparative analysis of a luminaire design on two different mission profiles. The DT architecture provides a robust framework for inflating the design into the comprehensive digital representation of a luminaire. Once a design is finished and validated using the DT architecture, it could be easily adapted for being used in real-world operation conditions.

The mission profiles correspond to the yearly temperatures of the City of Lyon (France) and to Las Palmas de Gran Canaria (Spain). These two mission profiles are representative of continental and subtropical climates. This experimental design allows for the assessment of the luminaire under different operation conditions, and enables the designers to make decisions on the suitability of a luminaire for a given market, for instance, in terms of geography.

Subsequent sections detail the experimental setup used to create and test the DT of the luminaire. The simulation procedure is described, involving the operation of the DT under various conditions and the monitoring of key performance parameters. A range of reliability and energy efficiency metrics derived from these simulations is then presented. Finally, these metrics are analyzed and compared to draw conclusions about the relative performance of the LED devices in each geographical context.

6.1. Experimental setup

The luminaire design under investigation comprises three main components: the LED device, the enclosure, and the PCB. The LED device is a surface-mount device (SMD) type with a 3535 footprint whose characteristics are shown in Table 4. The enclosure and the PCB are designed to be compatible with selected LED footprint, ensuring a consistent setup across the design.

The enclosure is designed to provide optimal thermal management and protection for the LED devices. It is made of an aluminum alloy to facilitate heat dissipation, thereby maintaining the LED devices' operating temperature within adequate range. The specific dimensions and design features are presented in Fig. 8.

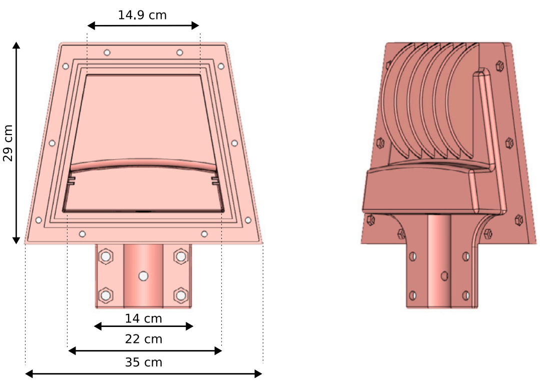

Fig. 8. 3D CAD model of the luminaire's housing.

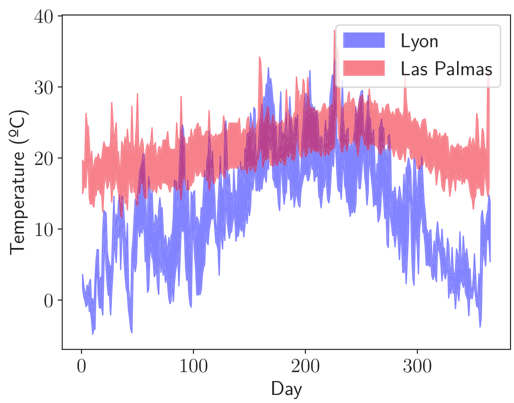

Fig. 9. Temperature profile. The graph depicts the maximum and minimum temperatures on each day of the year.

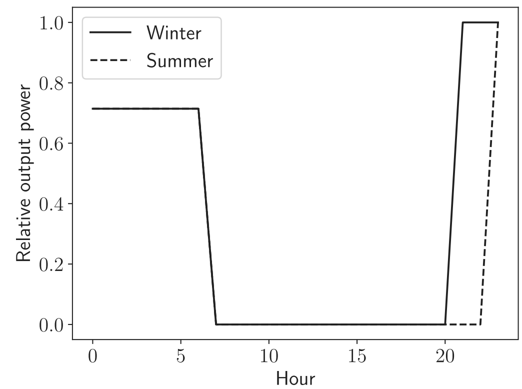

Fig. 10. Switching profile. Two different usage profiles are defined distinguishing between summer and winter operation.

Table 4
Information and parameters of the experimental setup.

Element	Property	Value
LED	Footprint V_f @ 85 °C, 1 A ϕ_{lum} @ 85 °C, 1 A L_{70} @ 85 °C, 1 A Pump wavelength Type $R_{th,js}$	3535 2.9 V 310 lm > 50 kh 450 nm Warm white (3000 K) 3 K/W
PCB	Type Number of LED	Metal core 16 in series
Enclosure	Material	Aluminum 6063
Secondary optics	Material	PMMA

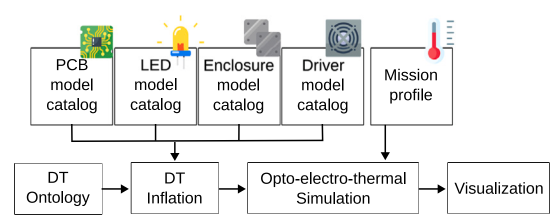

Fig. 11. Flow diagram of the simulation procedure.

The PCB serves as the platform for mounting the LED devices and provides the electrical connections necessary for its operation. It is designed to be compatible with the electrical characteristics of the LED devices and the power supply requirements of the luminaire. The layout of the PCB is optimized to ensure efficient power distribution and minimize electrical losses. In this example use case, 16 LED devices are arranged in series.

The mission profiles for the simulations are defined based on the typical operating conditions for a street lighting application in Lyon and Las Palmas de Gran Canaria (Fig. 9). This includes temperature variations throughout the year, ranging from a minimum of −10 °C in winter to a maximum of 40 °C in summer in Lyon, and between 15 °C and 35 °C in Las Palmas de Gran Canaria. The switching profile for the luminaire is also defined, taking into account the varying daylight hours throughout the year. The luminaire is programmed to operate at full power during the twilight hours, dim to 70% power during the night, and switch off during daylight hours. Fig. 10 depicts this scheme.

6.2. Simulation procedure

The simulation procedure is illustrated in Fig. 11 and begins with the creation of the DT for the luminaire using the previously defined ontology. The DT is a comprehensive digital representation of the luminaire, incorporating the LED device, the enclosure, and the PCB. The DT includes all the relevant parameters and their associated models, as defined in the ontology.

The DT is managed using a custom-made software platform that allows for the manipulation of the parameters and the running of the simulations. The platform is able to inflate the DT based on a catalog of devices compatible with the PCB layout (locally stored), connect to a cloud-based service to run thermal simulations for acquiring the resistor network of Eq. (7), and solving the electro-thermal equations of the LED branch according to the mission profile. The current implementation is supported by a schema-less database in order to provide enough flexibility as the ontology definition is expected to scale up in the near future to accommodate information from the full lifecyle. Once a specific luminaire's DT is instantiated, its RDF definition is converted to a JSON-like structure compatible with the database. Classes and individuals are directly translated into key–value pairs, whilst the object properties are converted employing the database's referencing system between documents (e.g., MongoDB's ObjectID). This pipeline does not interfere with the ontology since no reasoning is needed after the luminaire's DT is generated. The platform also provides a user-friendly interface for adjusting the parameters, running the simulations, and visualizing the results. It also includes tools for data analysis and reporting, facilitating the comparison of the performance metrics for the design operated in the two mission profiles.

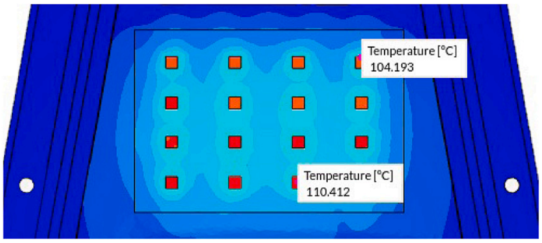

Fig. 12. Results of the thermal simulation. A heating power of 1 W was assumed on each LED, whilst a convective heat flow of 24 W·K·m^{-2} was configured at the rear heatsink.

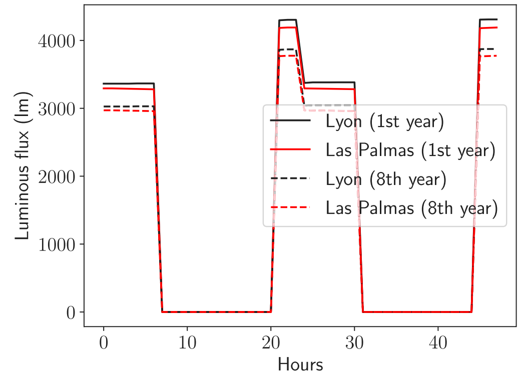

Fig. 13. Luminous flux profile with hourly resolution.

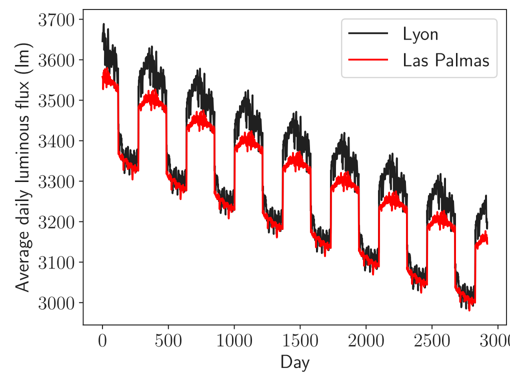

Fig. 14. Daily-averaged luminous flux.

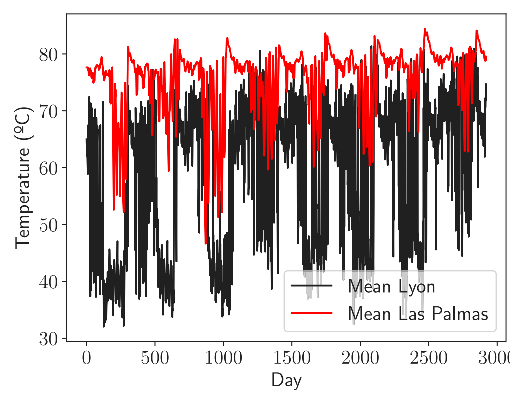

Fig. 15. Evolution of the average temperature of the LED devices.

6.3. Metrics

The performance of the luminaire is evaluated based on several key metrics, which are derived from the simulations run on their respective mission profiles. These metrics provide a comprehensive assessment of the LED devices' performance in terms of their light output, thermal management, and energy efficiency.

- **Radiant Flux**. Radiant flux, the total light emitted by a luminaire, is essential for tracking its light output. It helps monitor changes in LED devices' output over time under specific operating conditions, providing insight into LED degradation and its effect on overall luminaire performance.
- **Average junction temperature**. The average operating temperature of the LED devices is crucial for monitoring their thermal performance. Tracking this metric can help pinpoint potential thermal problems that could impair the LEDs' efficiency or longevity.
- **Optical efficacy**. The ratio of radiant flux to electrical power consumption represents the energy efficiency of LED devices. Tracking this optical efficacy over time reveals changes in the LEDs' energy efficiency under operating conditions, helping to spot potential efficiency issues and informing improvement strategies.

6.4. Results

The first step in order to perform the aforementioned simulations using the inflated DT and the two mission profiles is estimating the thermal resistor network. In order to achieve this, a heat transfer simulation using Simscale's cloud was carried out [44] (Fig. 12).

It can be observed that the thermal cross-talk between LED devices is negligible by design. Therefore, the matrix from Eq. (7) can be assumed diagonal. It can be also observed that the upper devices on the PCB are slightly colder than the lower ones (almost 8 degrees of difference), suggesting that those devices may contribute faster to the overall aging of the luminaire.

Using the estimated matrix and the *a priori* known $R_{th,js}$ values of the LED devices, the simulation on the two different mission profiles performed. Fig. 13 depicts 48 h of operation since the 1st day of year 1 and year 8 for both locations. It can be observed that after 8 years of operation under the corresponding mission profiles, the light output has diminished according to the aging of the devices (approximately 12% after 8 years of operation).

Analyzing long-term degradation trends (Fig. 14), Lyon shows higher winter light output than Gran Canaria, attributed to LED thermal sensitivity. Nonetheless, despite their different temperature profiles, both locations exhibit similar aging trends due to their similar yearly-averaged temperatures.

The analysis of Fig. 15, which depicts the time evolution of the average temperatures of the LED devices shows up notable differences. Nonetheless, Lyon's continental climate and Las Palmas' subtropical one result in a difference of 15 °C on the average junction temperature (75.6 °C vs 60 °C). In addition, a slight increment on the average temperature can be also noticed due to the loss of efficiency and consequent self-heating increase. Finally, the optical efficacy follows a similar trend to the luminous flux as expected (Fig. 16).

The average temperature metric offered a view into the thermal performance of the luminaire design. The design, subject to two different profiles maintained an average temperature within the optimal range for LED operation, indicating effective thermal management strategies in the luminaire design.

The flux over time provided insights into the light output of the LED devices and their degradation over time. Both simulations demonstrated a gradual decrease over the simulation period, consistent with the expected behavior of the devices. Related to that, the optical efficacy over time metric revealed how the energy efficiency changed over the course of the simulation. Furthermore, the results are well aligned with real-world experiments from the literature [45,46].

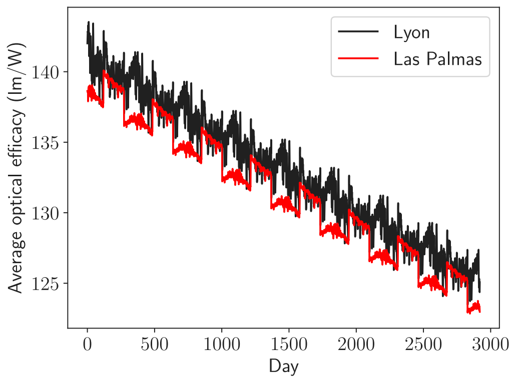

Fig. 16. Evolution of the average optical efficacy of the luminaires.

These results provide a comprehensive view of the performance of the luminaire design under two different mission profiles, covering aspects of light output, thermal management, and energy efficiency. Their alignment with the existing literature reinforces the validity of the DT and its potential as a tool for performance assessment and decision-making in the lighting industry.

7. Conclusions

In this paper, an ontology-based DT architecture for the lighting industry has been developed, capturing not only the relationships between the various elements that constitute a luminaire but also their intricate opto-electro-thermal interactions. Moreover, the ontology aims to maps out the full lifecycle of a luminaire, considering the potential agents involved at each stage, thereby supporting scalability and facilitating industry adoption. The ontology's complexity, as indicated by metrics such as SOV, ENR, TIP, and EOG, demonstrates its detailed and comprehensive nature whilst suggesting opportunities for further refinement and optimization in future iterations. In addition to the detailed ontological representation, the analysis encompasses the topology and connectivity within the DT architecture, offering a more holistic view of the luminaire's operational framework.

The experimental validations of this ontology-based DT approach confirm its effectiveness and alignment with existing literature. The conducted experiments, based on the performance comparison of a given luminaire subject to two different mission profiles, provide empirical evidence of the DT's ability to accurately replicate and analyze real-world luminaire behavior. This validation not only underscores the practicality of the ontology-based DT architecture but also paves the way for its continued evolution and application in the lighting industry, enhancing design, operation, and analysis of lighting systems.

7.1. Limitations and future work

The ontology-based DT architecture shows potential but has limitations that require further exploration. Specifically, the current models mainly consider temperature and driving current, but overlook other influential factors like humidity and dust. Therefore, expanding the ontology to include these elements could give a broader perspective on luminaire performance under real-world conditions.

Another current limitations include a heavy reliance on simulation data and a static luminaire design, potentially hindering the representation of real-world complexity. Future development will integrate field data and activate real-time monitoring, improving prediction accuracy. Also, by using the DT for design optimization, it could facilitate the development of custom lighting solutions that meet specific performance requirements, maximizing energy efficiency, reliability, and other characteristics.

Although the current work uses third-party cloud services for thermal simulations, the DT was locally operated, posing scalability and accessibility challenges. Future efforts could focus on creating user-friendly interfaces, implementing cloud-based platforms, and standardizing protocols. This will promote the ontology-based DT's widespread adoption in the lighting industry, enabling stakeholders like designers, manufacturers, and policymakers to harness DT capabilities and foster innovation.

Furthermore, the present ontology-based DT architecture, while apparently robust in its current form, acknowledges the necessity to encompass a wider set of dynamic environmental factors and user-centric aspects in future iterations. Upcoming versions will look to integrate more complex dynamic lighting conditions that go beyond temperature and driving current to include variables like humidity, dust, and aerosols, offering a more comprehensive model of luminaire performance in diverse environments. Additionally, there will be a focus on incorporating melanopic response analysis to better understand the impact of lighting on human circadian rhythms. This will be achieved by enhancing the ontology with models that evaluate light's biological effectiveness, aligning with evolving insights in light and health research. These advancements aim to refine the DT's predictive accuracy and optimize luminaire design for both energy efficiency and human well-being, ultimately contributing to the creation of more adaptive and personalized lighting solutions.

CRediT authorship contribution statement

Victor Guerra: Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Benoit Hamon:** Writing – original draft, Validation, Software. **Benoit Bataillou:** Supervision, Funding acquisition. **Adwait Inamdar:** Writing – original draft, Visualization, Validation. **Willem D. van Driel:** Writing – review & editing, Supervision, Funding acquisition, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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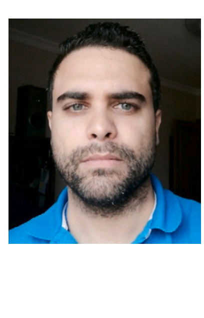

Dr Victor Guerra Graduating from Universidad de Las Palmas de Gran Canaria (ULPGC) with a degree in Telecommunication Engineering and a Ph.D. in Cybernetics and Telecommunication, Dr. Víctor Guerra Yánez boasts an extensive track record spanning over a decade in the field of Photonics Technology and Communications. His work traverses Optical Wireless Communication, Optical Camera Communication, Internet of Things, and their intersection with Deep Learning. His professional experience comprises an array of projects, including 4 H2020 initiatives and other collaborative research efforts. He has also authored over 75 scientific publications encompassing a range of formats.

Dr Benoit Hamon, Ph.D., is a seasoned professional in the field of LED technology and reliability. Currently serving as a Senior Consultant at Pi Lighting in Switzerland, Dr. Hamon offers his expertise in product development and reliability, providing strategic advice and technology scouting for clients across Europe and North America. He has a rich history in the LED industry, having worked as a Development Engineer at Philips Professional Lighting Solutions, where he was instrumental in creating LED technology roadmaps and providing technical support for LED commodity teams. Dr. Hamon earned his Ph.D. from Philips Lighting/CEA Léti, where he specialized in the mechanisms of LED reliability. He has also contributed to the field through various publications and patents, and has been a speaker at numerous conferences.

Dr Benoit Bataillou, who holds a Ph.D. in Semiconductor Physics, has spent over 15 years in the semiconductor and LED industry. His primary expertise lies in Solid State Lighting (SSL), statistics, and standard industry models. Co-founding three companies, Bataillou has been involved in developing scientific tools and methodologies for various sectors. His portfolio includes 20 patents, and he has been part of the LED market evolution since the early GaN experiments in 1999. His skills include connecting different areas of expertise and a continuous desire for learning, which has enabled him to explore new areas and solve complex problems. His contributions range from strategy formulation and platform development to knowledge sharing. Today, Bataillou continues his work in his field, encouraging progress and collaboration.

Adwait Inamdar is a Ph.D. student at the Department of Microelectronics, TU Delft, Netherlands. He pursued B.Tech. in Mechanical Engineering (VNIT Nagpur, India) and M.Sc. in Computational Engineering (Ruhr-University Bochum, Germany). His current work is in the field of microelectronics reliability, focusing on the physics-of degradation and Digital Twin technology for prognostics and health management of electronic components.

Prof Dr Ir Willem D. van Driel graduated as a mechanical engineering at Technical University of Eindhoven and received a Ph.D. degree from Delft University of Technology, The Netherlands. He has a >25 year track record in the reliability domain. Application areas range from healthcare, gas and oil explorations, semiconductors. His current position is Fellow Scientist at Signify (formerly Philips Lighting). Besides that he holds a professor position at the University of Delft, The Netherlands. His scientific interests are solid state lighting, microelectronics and microsystems technologies, virtual prototyping, virtual reliability qualification and designing for reliability of microelectronics and microsystems. He is chair of the organizing committee of the IEEE conference EuroSimE. He has authored and co-authored more than 350 scientific publications, including journal and conference papers, book or book chapters and invited keynote lectures.