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OntoFreya: A Power Distribution Ontology for Electric Metrics Classification

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Abstract: Power utilities demand large volumes of data used in power distribution networks. Among them are parameters representing possible technical failures, such as network's short circuit current and voltage sag. Specialists find these parameters and detect technical failures. However, this process can become time-consuming. Thus, this article proposes an ontology called OntoFreya, which classifies voltage, current, or any electric metric, following the definitions of the regulatory agencies and reducing the time spent on this task. A series of 4402 axioms, 132 classes, and 40 data properties comprises OntoFreya. The ontology automatically inferred classifications for four hundred readings from energy samples, validating OntoFreya across three scenarios. The first and second scenarios classified current in amperes, and the third classified voltage in per-unit system (pu). The scenarios showed that OntoFreya automates the classification of electric metrics, reducing specialists' time in detecting technical failures in a distribution network.

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1 Introduction

Energy has been a basic human need in all available forms, enabling sustenance and development. Given this, humankind has always sought energy sources to supply this demand. In this context, electric energy is one of the most viable solutions. Due to the versatility of production, transformation into other energy sources, and use, electric energy has become a strategic resource for the socio-economic development of any region or nation. After decades of development in the generation, transmission, and distribution of electric energy, the current focus is on the quality of supplied energy enabling optimized performance, and reliability [Lee et al., 2022].

The Smart Grid (SG) advent allowed more assertive methods for electricity generation and distribution [Zheng et al., 2021, dos Santos Costa et al., 2022]. Intelligent controls and data analysis enable the detection of deviations and increase the system's quality. New developments focused on data from electrical distribution systems and Artificial Intelligence techniques allowing the prediction of electrical metrics and problem detection regarding an electrical grid [Nti et al., 2021].

The advancement of technologies aimed at electrical power distribution systems helped decision-making for remote-controlled equipment and produced large amounts of data in this domain. Consequently, these data from the equipment or the equipment's ambient require adequate interpretation strategies to increase the system's reliability [Zainab et al., 2021, dos Santos Costa et al., 2023].

In order to map these factors occurring in the same ambient of the equipment, the usage of ubiquitous computing can be an alternative. Ubiquitous computing considers context awareness one of the aspects for dealing with information [Barbosa, 2015, Aranda et al., 2022]. Context characterizes information related to an entity (i.e., equipment), such as voltage regulator, and information related to this entity, such as voltage, current, power, temperature, and humidity. Contexts have attributes, such as an identity (i.e., unique identification), status, date, and time. All this information helps to determine the chronological order of events, and this chronological order composes the context histories [Aranda et al., 2021].

Mapping a domain may outline relevant context information. Incidentally, one well-accepted technique for representing a domain is called ontology. Ontology is a shared understanding representation of entities, relations, functions, axioms, and instances. This information is relevant for representing the domain organization [Pradeep et al., 2021, Bavaresco et al., 2024]. One of the characteristics of ontologies is the ability to make inferences using boolean operators such as "and", "or" and "not" in properties and relationships. The ontology allows to constrain cardinalities and configure data ranges. Thus, any individual who fills in the logical expression is a member of that concept. Ontologies' conception includes the idea of sharing and expanding a domain representation. Generally, the OWL language can represent the ontology supporting semantic interoperability for exchanging and sharing knowledge of information between different systems [Larentis et al., 2021, Helfer et al., 2025].

Therefore, this work presents the modeling and the results obtained with an ontology called OntoFreya that classifies electrical metrics according to the readings of the electrical distribution network equipment. The main contribution of this work lies in the automatic classification of energy metrics. Usually, specialists perform this task, and the automatic classification reduces the time-consuming activity. Particularly, the current literature does not propose a formal ontology for the power distribution domain. A power distribution ontology can help to represent the domain and map relevant information. In addition, the proposed ontology considers real data and the ambient equipment to perform inferences and classifications.

OntoFreya is an ontology that would be part of a computational model called Freya. The Freya model intends to predict electrical amounts that would be inferred by OntoFreya. The Freya model is in development. The model and OntoFreya will be evaluated and used in operation jointly with two power utilities companies [1] [2]. This article is partially based on the Ph.D. thesis of the first author entitled "OntoFreya: A Power Distribution Ontology for Electric Metrics Classification", defended at the University of Vale do Rio dos Sinos (UNISINOS) [Aranda, 2024]. This article has five sections. Section two describes related works. Section three presents the ontology modeling process. Section four shows the results of the ontology validation, and, finally, the last section concludes with the final remarks of this work.

2 Related Works

The use of ontologies to support SG systems is an emerging field of research. Hence, this study adopted the Snowball Sampling (SS) technique [Leighton et al., 2021, Aranda et al., 2019]. The SS allowed finding related studies that use ontologies in the SG domain. The SS technique involves reading the references in a paper and searching for works related to the research study.

Salameh et al. [2019] proposed an ontology to resolve the interoperability issues related to SG systems. Since each component of an SG could have syntactic and semantic differences, the authors use the ontology to unify SG components. Schachinger et al. [2016] developed an ontology to work as a middleware between SGs and Building Energy Management Systems (BEMS). The ontology works as a semantic translator of the SG components to the BEMS, allowing SG data input through management systems.

Zanabria et al. [2019] presented the EMSOnto, an ontology to support SG automation systems. The authors previously created a Power System Automation Language

(PSAL) to validate the inferences resulting in SG automation suggestions. The study of YeeChong et al. [2020] approaches a methodology to create ontologies for

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[1] https://www.certaja.com.br/energia/

[2] https://www.ceee.com.br/home

SGs. Considering all the domain aspects of the SG, the author's method intend to become a gateway to semantically translating SG information.

The criteria for performing *inferences*, use of *SPARQL* queries, *domain* application, type of *evaluation*, and consideration of *context-aware* data allow the comparison between OntoFreya and related works. All related works focus on SG systems in general, while OntoFreya focuses on energy classification of power distribution networks. Additionally, none of the works uses context histories to make inferences. Usually, the ontologies literature advises extending an existing ontology [Li et al., 2019], but in this case, the entities represent different domains, demanding the creation of a new ontology.

Regarding the related studies and the comparison criteria, three use inferences to support applications [Salameh et al., 2019, Schachinger et al., 2016, Zanabria et al., 2019]. The study of Salameh et al. [2019] is the only one that uses SPARQL queries. All works applied ontologies in generic SG applications, energy generation, and SG Automation. Two of the studies evaluate the ontologies with Synthetic data (simulated or manually inserted) [Salameh et al., 2019, Schachinger et al., 2016] and one uses third-party energy dataset [Zanabria et al., 2019]. Finally, neither of the works considers context data regarding the SG entities. Furthermore, related works did not apply equipment data or real network data for validation. Since ontologies use domain data to reason about entities, this is also a differential of OntoFreya compared to the related works.

3 Ontology Modelling

Ontology modeling can follow various methodologies, with some well-established approaches serving as foundational references—most notably, Methontology [Fernandez-López et al., 1997]. This methodology is widely recognized for its structured and systematic process, and it has influenced many subsequent approaches that build upon its principles while introducing refinements tailored to specific domain requirements.

For instance, Smirnov et al. [2021] emphasizes that ontology development is inherently iterative, requiring continuous alignment between conceptual elements and the domain they aim to represent. The methodology applied in this work follows the standards established by Methontology while incorporating key adaptations. These modifications enhance aspects such as modularity, scalability, and integration with real-world data sources, ensuring that the ontology is more adaptable to evolving power distribution scenarios [Smirnov et al., 2021]. Table 1 highlights the similarities and differences between Methontology and the methodology employed in this study.

Step	**Methontology**	**OntoFreya Methodology**
Specification	Defines ontology purpose, scope, and competency questions.	Defines ontology purpose and scope, identifies relevant

		concepts, and selects ontology aspects.
Conceptualization	Represents knowledge as a conceptual model, defining concepts, attributes, and relationships.	Defines concepts and relationships for each ontology aspect, ensuring alignment with domain-specific needs.
Formalization	Transforms conceptual model into an ontology expressed in a formal language.	Uses OWL for ontology formalization and ensures semantic correctness.
Implementation	Implements ontology using a development tool (e.g., Protégé).	Initially it used Protégé but migrated to OwlReady2 for better scalability and integration.
Evaluation	Validates ontology with competency questions and expert reviews.	Validation is performed with real-world data from power utilities and standards adopted by experts.
Integration & Reuse	Incorporates existing ontologies and ensures interoperability.	Focuses on modular ontology design, allowing flexible rule adjustments and adaptation to different power networks.

Table 1: Comparison between Methontology and OntoFreya approach

In order to adhere to the power distribution domain, the rules of the ontology follow the definition of Brazilian regulatory agencies. The rules can be modeled accordingly to the need of the regulatory agency. Since the distribution network analyzed in this work is in Brazil, the rules consider the regulations proposed by the Brazilian National Agency of Electric Energy (ANEEL) [ANEEL, 2016]. The distribution network has different types of equipments, but this study employed the voltage regulator VR-001 and the recloser REC-001. These two equipment are 10.5 km from the substation that serves three primary feeders - AL-001, AL-002, and AL-003.

The validation of OntoFreya's classification rules and structure was carried out with the participation of experienced domain experts from the power distribution sector. These professionals contributed with their practical knowledge and provided valuable feedback, ensuring that the ontology aligns with real-world operational conditions and regulatory standards. Table 2 presents the profiles of the experts involved in this process, highlighting academic backgrounds and areas of expertise relevant to power systems and smart grid technologies.

Academic Background	**Current Role and Expertise**
Bachelor Degree in Electrical Engineering, Specialist in Power Systems	Electrical Engineer; expertise in energy distribution networks and regulatory compliance
Bachelor Degree in Electrical Engineering, Specialist in Power Systems	Electrical Engineer; experience in smart grids and electrical systems planning
M.Sc. in Electrical Engineering, Specialist in Power Systems	Electrical Engineer; focus on maintenance, distribution systems, and grid monitoring
M.Sc. and Specialist in Renewable Energies	Senior Electrical Engineer at; specialist in power distribution system design and asset management
Ph.D. in Electrical Engineering, M.Sc. in Electrical Engineering	Professor and researcher, former engineer, expert in smart grids and distributed energy systems

Table 2: Experts involved in OntoFreya validation

ANEEL defines voltage values ranging between *adequate*, *precarious*, and *critic* according to the reference value of the equipment. The voltage rule considers the per-unit system (pu). For instance, VR-001 has the referenced value of 7967 volts in medium voltage, so in this case, the value of 7967 volts is equal to 1 pu. On the other hand, REC-001 uses parameters inserted in the supervisory system.

According to the load balance estimation of the power utility specialists, this equipment has a pick-up value of 80 amperes. The supervisory system considers a heavy load if the current surpasses 55% of the pick-up value, in this case, 44 amperes. Moreover, the level of loads *Light*, *Medium*, and *heavy* allow performing inferences regarding the recloser.

The OntoFreya which stands for Freya Ontology (since this project is related to a computing model called Freya) is available at a GitHub repository [3] with a public domain license. The ontology development considered the types of equipment and entities of a distribution network as classes. Each class has a context, measured electric metrics, and other information that can help to infer the entity classification, like temperature and humidity. The main entities identified in the distribution network and modeled into classes were *Voltage Regulator*, *Recloser*, *Substation Transformer*, *Weather Condition* (of the network in general), *Distributed Generation Unit*, *Capacitor Bank*, and *Customer*. Subclasses of the entities are *Voltage Regulator In*, *Voltage Regulator Out*, *Voltage Regulator Tap*, *Voltage Regulator Power*, *Voltage Regulator Context Data*, *Recloser Context Data*, *Recloser Voltage*, *Recloser Current*, *Recloser Power*, *Substation Transformer Power*, *Substation Transformer Context Data*, *Substation Transformer Voltage*, *Substation Transformer Tap*, *Stored Energy*, *Type of Consumer*, *Photovoltaic Production*, *Temperature*, *Sky*, *Storms*, *Preciptation*, *Humidity*, *Wind Speed*, *Solar Irradiance*, and *Pressure*.

The distribution network in the current proposal has an energy sample collected by supervisory systems. Each reading has *In* and *Out* in pu (for the voltage regulator) or % of pick-up current (for the recloser), date of reading, entity name, temperature, and humidity values. The last two, regarding weather, can affect the electric readings and are considered a piece of context information [Leighton et al., 2021]. This energy sample presents a hierarchy of entities within a domain and the properties defined by attributes of a type value. In this scenario, OntoFreya can assign result analysis of electrical sample readings from the established rules and automatically infer the classification of this sample.

The OntoFreya ontology was developed in the OWL language using the software Protégé in version 5.5 [Larentis et al., 2021]. All readings were disjuncts within each class group: *Adequate*, *Precarious*, and *Critic* for voltage and *Light*, *Medium*, and *Heavy* for current. In this way, an energy reading has at least one value for each type.

OntoFreya's design choices regard the domain of power distribution in Brazil, accordingly to the country's regulatory agencies. In OntoFreya, axioms define classes of electric metrics, converting amperes to a percentage of pick-up value for the recloser and pu for the voltage regulator. The rules to classify the pu_{in} or pu_{out} has three levels according to the inlet and outlet voltages. For example, Figure 1 shows the logical expression used in the equivalence axiom for that calculation. The previously mentioned rule means that if an instance (in this case, an electrical reading) that is a reading for a VoltageRegulatorVoltageIn (Class of voltage regulator, considering the voltage in reading) has a data property value (DVoltageRegulatorVoltageIn) presented in a double-digit number and greater or equal than 0.93 pu and lesser or equal than 1.05 pu, the reading will be inferred as the description (VoltageRegulatorVoltageAdequateIn), meaning that this reading, in this class has an adequate reading. Similar expressions define the *Critic* and *Precarious* levels,

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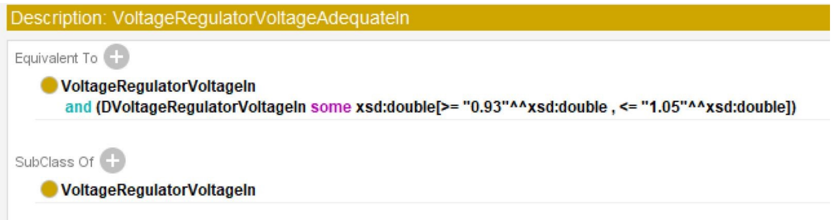
[3] https://github.com/jsaranda/OntoFreya

according to the ranges presented in the voltage table, in this specific example and for validation purposes. This logical expression verifies if the PU value is between 0.93 and 1.05 volts. The DVoltageRegulatorVoltageIn is the variable that is verified in the presented logical expression. Since in Protégé, the classes cannot have the same name of the data variables, as a pattern OntoFreya has the ”D” at the start of an axiom as a data variable.

Similarly, the recloser class applies the rule regarding the current reading. The proposed voltage rules shows that the recloser has different thresholds to infer from energy samples. Figure 2 shows the logical expression of the rule applied to recloser readings at the *Light* level.

OntoFreya also considers the context information of the recloser, the voltage regulator, or other main classes presented in this section. Each main class has the subclass Context Data, which contains temperature and humidity logical axioms to *Operational Temperature/Humidity* or *Non Operational Temperature/Humidity*. This inferences exemplify the inferences regarding context information according to the effects on the power distribution network [Leighton et al., 2021].



Description: VoltageRegulatorVoltageAdequateIn

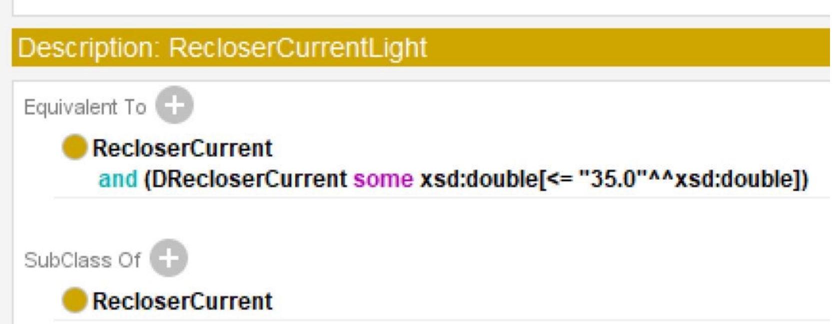
Equivalent To

VoltageRegulatorVoltageIn
and (DVoltageRegulatorVoltageIn some xsd:double[>= "0.93"^^xsd:double , <= "1.05"^^xsd:double])

SubClass Of

VoltageRegulatorVoltageIn

Figure 1: Logical expression in axiom for voltage regulator inference



Description: RecloserCurrentLight

Equivalent To

RecloserCurrent
and (DRecloserCurrent some xsd:double[<= "35.0"^^xsd:double])

SubClass Of

RecloserCurrent

Figure 2: Logical expression in axiom for recloser current inference

The classification thresholds adopted in OntoFreya, such as the 0.93–1.05pu interval for adequate voltage and values below 0.90pu for critical voltage, are grounded in both national and international standards and literature. The Brazilian Electricity Regulatory Agency (ANEEL) establishes in its PRODIST Module 8 that distribution systems must maintain voltage within the range of 0.93 to 1.05pu under normal operating conditions, with deviations below 0.90pu or above 1.05pu considered critical events [IEEE, 2018].

Internationally, the IEC 60038 standard defines a nominal voltage tolerance of ±10% for low and medium voltage systems, which corresponds to a per-unit range of 0.90 to 1.10pu [IEC, 2009]. Similarly, IEEE Std 1547-2018 establishes a continuous voltage operation band of approximately 0.95 to 1.05pu for distributed energy resources (DERs), with a broader allowable range of 0.88 to 1.10pu during transient conditions [IEEE, 2018]. These standards confirm the semantic and technical adequacy of the thresholds used in OntoFreya.

Recent scientific research supports these normative values. For instance, Attia et al. [2025] analyze power quality challenges in distribution systems and emphasize the importance of voltage regulation within ±5% to avoid equipment degradation. Additionally, a 2025 technical report from the Electric Power Research Institute (EPRI) reinforces the adoption of a 1.05pu upper limit to prevent overvoltage in DER-integrated radial systems [EPRI, 2025]. These regulatory and empirical foundations provide robust justification for OntoFreya's classification logic and ensure that the ontology is semantically valid and interoperable with global practices in smart grid monitoring and analysis.

Building upon this normative framework, the practical process of data acquisition and transformation was designed to ensure that OntoFreya receives consistent information reflecting real-world operational conditions. The ontology is populated with semantically enriched data derived from measurements collected by supervisory control systems (SCADA) of power distribution utilities. These raw readings, initially expressed in physical units such as volts and amperes, are normalized into domain-specific representations—specifically, per-unit (pu) values for voltage and percentages of the pickup threshold for current. For example, a voltage reading of 7650 V for a device rated at 7967 V is converted to 0.96 pu, while a current reading of 36 A with a pickup threshold of 80 A is represented as 45%. Each record also includes a timestamp and the equipment identifier (e.g., VR-001 for voltage regulators and REC-001 for reclosers).

In addition to electrical measurements, contextual environmental data such as ambient temperature and humidity is retrieved from the OpenWeather API using the geographic coordinates of each monitored device. These contextual values are aligned with the electrical data by timestamp and incorporated into OntoFreya as attributes of the ContextData subclasses, enabling inference of context-dependent conditions such as Operational Temperature or Non Operational Humidity.

To ensure data integrity, all SCADA and weather data undergo preprocessing, including removal of incomplete or inconsistent records, formatting of timestamps to ISO 8601, validation of equipment identifiers, and synchronization based on geolocation and time. After preprocessing, a Python script developed with the OwlReady2 library automatically generates individuals in the ontology. Each data entry is transformed into an instance that is assigned to appropriate semantic classes (e.g., Recloser Current Medium, Voltage Regulator Voltage Adequate In) through OntoFreya's reasoning process.

For instance, a voltage reading of 0.89 pu for equipment VR-001 is inferred as VoltageRegulatorVoltageCriticIn, as it falls below the 0.90 pu threshold. Likewise, a humidity level of 87% may trigger the inference of the class NonOperational Humidity. This structured transformation process ensures that OntoFreya receives both normalized and context-aware data, supporting accurate and meaningful reasoning in various power distribution scenarios.

4 Evaluation and Results

This work evaluates OntoFreya based on scenarios. Scenarios are strategies to evaluate ubiquitous applications and context-aware systems [Barbosa et al., 2018]. The first scenario comprises the recloser equipment and considers the actual parameters and data of a distribution network provided by the Certaja power utility [4]. Future validations will be applied in the Certaja power utility network.

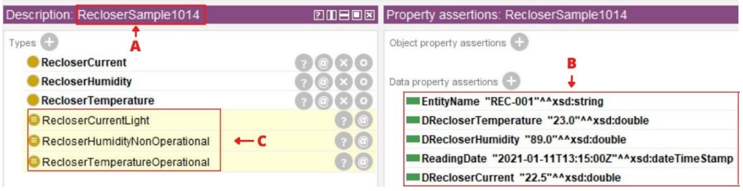
The second scenario is similar to the first one, with different parameters. A change in parameters could show other outputs regarding the recloser equipment. Finally, the third scenario evaluates the ontology with the voltage regulator entity. The Certaja company stored and provided data and equipment parameters in excel files. Adding the context data (temperature and humidity) from a weather API [5] allows the context inferences.

Due to performance limitations on the protégé software, OntoFreya can only create 200 energy samples for each type of equipment, totaling 400 individuals. Finally, a python script adds each individual to the ontology XML file. The following subsections show the results of the inferences in the scenarios mentioned earlier.

4.1 Scenarios 1 and 2 - Recloser

The creation of instances called individuals in the protégé software covers the range of load readings classification of a recloser. The evaluation takes place with the automatic reasoning process. Then the logical expressions process each individual with the reasoner HermiT, an ontology reasoner for the OWL language included in the protégé.

Figure 3 shows the result for the energy reading classification of the sample 1014, the letters indicate strategic information in the figure. One of the individual instances of the readings is the *Recloser Sample 1014* (A), which has an entity name of *REC-001*, temperature of *23* degrees celsius, *89%* of humidity, the date of the reading of *11-January-2021 at three o'clock* and a current of *22.5%* of the pick-up value (B). The classes *Recloser Current Light*, *Recloser Humidity Non-Operational*, and *Recloser Temperature Operational* are the results of this individual inference (C).



RecloserCurrent
RecloserHumidity
RecloserTemperature
RecloserCurrentLight
RecloserHumidityNonOperational
RecloserTemperatureOperational

EntityName "REC-001"^^xsd:string
DRecloserTemperature "23.0"^^xsd:double
DRecloserHumidity "89.0"^^xsd:double
ReadingDate "2021-01-11T13:15:00Z"^^xsd:dateTimeStamp
DRecloserCurrent "22.5"^^xsd:double

Figure 3: Recloser inference result for Scenario 1

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[4] https://www.certaja.com.br/energia/

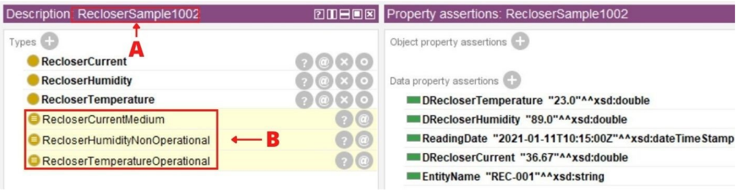
[5] https://www.meteomatics.com/en/weather-data/

This inference considers the voltage rules defined by ANEEL. The *Recloser Current Light* class represents readings with a current below 35% of the pick-up value. The *Recloser Current Medium* represents readings with a current between 35% and 55% of the pick-up value. Finally, the *Recloser Current Heavy* represents the readings with a current over 55% of the pick-up value.

In addition to inferences related to the electric metrics classification, OntoFreya allows domain representation to other languages such as RDF that queries with SPARQL, similar to SQL, but with greater expressiveness. Running a search for instances with SPARQL query classified the results as *Recloser Current Heavy* or *Recloser Current Medium*. The classification rules were in the query's filter field in this case (A). This energy status occurred together with all the readings, on 11-January-2021, one at 09:45 and another at 22:15 (B). This search example allows the specialists to identify when one of the equipment is with a *Medium* or *Heavy* load (C).

Since only two of 200 readings are under *Recloser Current Medium* or *Recloser Current Heavy* classification, most readings are under the *Recloser Current Light* classification in Scenario 1. This result means that a Recloser with a pick-up value of 80 amperes is a good choice for this network. Alternatively, for Scenario 2, the specialists consider a Recloser with a pick-up value of 60 instead of 80 amperes. This change means that the 55% of the current threshold decreases and affects every classification.

Nonetheless, all rules from Scenario 1 apply to Scenario 2 – except the pick-up value. Figure 4 shows the inferences about sample 1002. In this new round of inferences, the *Recloser Sample 1002* (A) classification changed from *Light* to *Medium* (B).



DRecloserTemperature "23.0"^^xsd:double
DRecloserHumidity "89.0"^^xsd:double
ReadingDate "2021-01-11T10:15:00Z"^^xsd:dateTimeStamp
DRecloserCurrent "36.67"^^xsd:double
EntityName "REC-001"^^xsd:string

Figure 4: Recloser inference result for Scenario 2

The SPARQL query illustrates a new search for instances classified as *Recloser Current Medium* or *Recloser Current Heavy* (A). Again, the classification rules were in the query's filter field. This time 35 readings match the *Medium* or *Heavy* status (B) compared to only 2 in Scenario 1. This result shows that OntoFreya can help specialists find issues when the network equipments parameters are not well estimated – such as the pick-up value for the recloser. The use of the historical record of equipments as individuals of the ontology allows the representation of the domain's current behaviors.

To summarize the impact of modifying the pickup value between scenarios, Table 3 presents a comparative view of the classification distribution across current levels. While Scenario 1 uses a pickup value of 80 Amperes, Scenario 2 applies a reduced threshold of 60 Amperes, altering the load classification criteria accordingly. The table displays the percentage of readings classified as *Light*, *Medium*, and *Heavy* in each scenario, along with the variation observed between them. The data show that in Scenario 1, with the higher pickup threshold, the majority of readings (92%) fall into the *Light Current* category, with only 6% and 2% classified as *Medium* and *Heavy*, respectively. However, when the pickup threshold is reduced to 60 A in Scenario 2, the classification distribution changes significantly: *Light Current* drops to 72%, while *Medium* and *Heavy* increase to 20% and 8%, respectively. These shifts indicate that lower thresholds lead to a stricter interpretation of what constitutes a medium or heavy load. Such variations reflect OntoFreya's ability to semantically adapt its reasoning based on parameter changes, which is essential in real-world environments where equipment settings may vary across different substations or over time. This example also illustrates how changes in equipment parameters, such as the pickup threshold, can directly affect semantic classification outcomes when applied to real operational data. By analyzing these effects, utility operators gain deeper insights into how configuration choices influence system behavior, thereby supporting more informed decisions regarding network settings and asset management strategies.

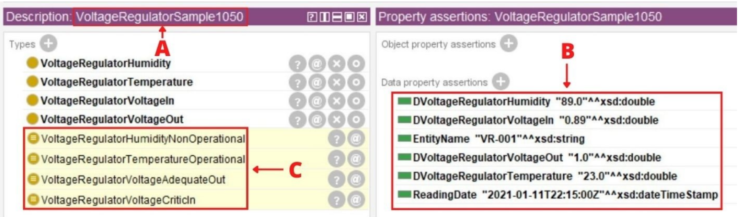
4.2 Scenario 3 - Voltage Regulator

Scenario 3 has 200 instances of voltage inlet and outlet readings converted to pu. This difference happens because the voltage regulator has pu_{in} and pu_{out} readings. When the recloser's purpose is to avoid high current load in the network, the voltage regulator receives a *critic* or *precarious* value of voltage in the pu_{in} of the equipment and regulates the voltage giving the network an *adequate* value of pu_{out}.

Classification Level	Scenario 1 (80 A Pickup)	Scenario 2 (60 A Pickup)	Variation
Light Current	92%	72%	–20%
Medium Current	6%	20%	+14%
Heavy Current	2%	8%	+6%

Table 3: Comparison of classification outcomes between Scenario 1 and Scenario 2 (Recloser)

Figure 5 shows the result for the energy reading classification of the sample 1050. One of the individual readings instances is the *Voltage Regulator Sample 1050* (A) with *89%* of humidity, *Voltage In* of *0.89* pu, an entity name of *VR-001*, *voltage Out* of *1.0* pu, a temperature of *23* degrees celsius, and the date of the reading of *11-January-2021 at 22:15* (B). The classes *Voltage Regulator Humidity Non-Operational*, *Voltage Regulator Temperature Operational*, *Voltage Regulator Voltage Adequate Out*, and *Voltage Regulator Voltage Critic In* are the results of the inference of this individual in Scenario 3 (C).



Description: VoltageRegulatorSample1050

Types
VoltageRegulatorHumidity
VoltageRegulatorTemperature
VoltageRegulatorVoltageIn
VoltageRegulatorVoltageOut
VoltageRegulatorHumidityNonOperational
VoltageRegulatorTemperatureOperational
VoltageRegulatorVoltageAdequateOut
VoltageRegulatorVoltageCriticIn

Property assertions: VoltageRegulatorSample1050

Object property assertions

Data property assertions
DVoltageRegulatorHumidity "89.0"^^xsd:double
DVoltageRegulatorVoltageIn "0.89"^^xsd:double
EntityName "VR-001"^^xsd:string
DVoltageRegulatorVoltageOut "1.0"^^xsd:double
DVoltageRegulatorTemperature "23.0"^^xsd:double
ReadingDate "2021-01-11T22:15:00Z"^^xsd:dateTimeStamp

Figure 5: Voltage Regulator inference result for Scenario 3

Proceeding with the same validation patterns of Scenarios 1 and 2, SPARQL query shows a search for instances classified as *Voltage Regulator Voltage Critic In* (A). The search for a Critical status applying the rules in the query filter identified 25 results (B).This result brings electrical readings which had a voltage regulator in input which less than 0.90 PU OR greater than 1.05 PU. This means that from this electrical readings dataset had 25 events of critical load. Since each reading occurs in a 15-minute window, the distribution network could be outside of the thresholds during 6 hours and 15 minutes (15 minutes * 25 events).

4.3 Ontology Development and Performance Evaluation with OwlReady2

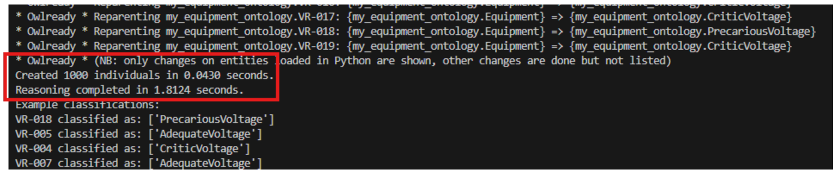
Traditional ontology modeling tools, such as Protégé, often encounter scalability limitations when processing large datasets. Addressing this challenge, OntoFreya was reimplemented using the OwlReady2 library in Python, enabling more efficient data handling and seamless integration with tools for data analysis, automation, and real-time processing.

The OwlReady2 library supports the dynamic creation of ontology instances and allows the insertion of thousands of individuals within seconds. An evaluation involving the insertion of 10,000, 20,000, and 40,000 individuals yielded execution times ranging from 0.75 to under 3 seconds. Figure 6 shows results that highlighted the system's ability to manage large volumes of data in a short time of processing. For comparison, a typical year of equipment operation generates approximately 35,000 records. This evidence confirms the feasibility of using OwlReady2 for real-time and large-scale ontology-based classification.

```
PS C:\owlCode> & C:/Users/ADM JSARANDA/AppData/Local/Programs/Python/Python312/python.exe c:/owlCode/ontology_performance.py
Inserted 10000 individuals into the ontology in 0.7552 seconds.
Example of some individuals:
REC-014
REC-007
REC-004
VR-011
REC-001
PS C:\owlCode> & C:/Users/ADM JSARANDA/AppData/Local/Programs/Python/Python312/python.exe c:/owlCode/ontology_performance.py
Inserted 20000 individuals into the ontology in 1.5145 seconds.
Example of some individuals:
VR-006
VR-008
VR-011
REC-005
VR-012
PS C:\owlCode> & C:/Users/ADM JSARANDA/AppData/Local/Programs/Python/Python312/python.exe c:/owlCode/ontology_performance.py
Inserted 40000 individuals into the ontology in 2.9933 seconds.
Example of some individuals:
VR-017
REC-007
VR-015
VR-003
REC-008
```

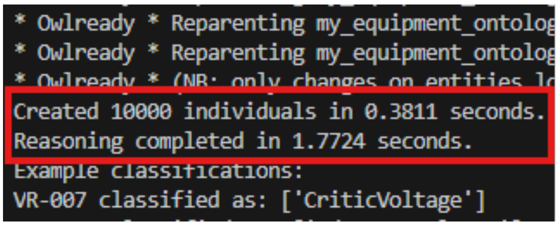
Figure 6: Performance evaluation of ontology instance insertion using OwlReady2

OntoFreya delivers not only data insertion but also reasoning performance. In power utility operations, experts typically take between 30 seconds and 1 minute to manually verify a single electrical reading, depending on the complexity and contextual factors involved. OntoFreya improves this process by classifying thousands of readings in a few seconds. Reasoning evaluation confirmed this result. When processing 1,000 individuals, OntoFreya completed the reasoning task in under 2 seconds, as shown in Figure 7. Figure 8 shows that the reasoning time remained stable for 10,000 individuals, again completing in less than 2 seconds. Even with 40,000 individuals, OntoFreya maintained the results, completing the reasoning in under 2 seconds, as illustrated in Figure 9. These results demonstrate OntoFreya's ability to support large-scale, real-time data processing, enabling proactive monitoring, decision-making, and a reduction in the workload for technical specialists.



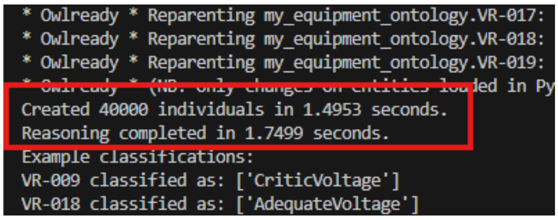
```
* Owlready * Reparenting my_equipment_ontology.VR-017: {my_equipment_ontology.Equipment} => {my_equipment_ontology.CriticVoltage}
* Owlready * Reparenting my_equipment_ontology.VR-018: {my_equipment_ontology.Equipment} => {my_equipment_ontology.PrecariousVoltage}
* Owlready * Reparenting my_equipment_ontology.VR-019: {my_equipment_ontology.Equipment} => {my_equipment_ontology.CriticVoltage}
* Owlready * (NB: only changes on entities loaded in Python are shown, other changes are done but not listed)
Created 1000 individuals in 0.0430 seconds.
Reasoning completed in 1.8124 seconds.
Example classifications:
VR-018 classified as: ['PrecariousVoltage']
VR-005 classified as: ['AdequateVoltage']
VR-004 classified as: ['CriticVoltage']
VR-007 classified as: ['AdequateVoltage']
```

Figure 7: Reasoning performance with 1,000 readings



```
* Owlready * Reparenting my_equipment_ontolog
* Owlready * Reparenting my_equipment_ontolog
* Owlready * (NB: only changes on entities lo
Created 10000 individuals in 0.3811 seconds.
Reasoning completed in 1.7724 seconds.
Example classifications:
VR-007 classified as: ['CriticVoltage']
```

Figure 8: Reasoning performance with 10,000 readings



```
* Owlready * Reparenting my_equipment_ontology.VR-017:
* Owlready * Reparenting my_equipment_ontology.VR-018:
* Owlready * Reparenting my_equipment_ontology.VR-019:
* Owlready * (NB: only changes on entities loaded in Py
Created 40000 individuals in 1.4953 seconds.
Reasoning completed in 1.7499 seconds.
Example classifications:
VR-009 classified as: ['CriticVoltage']
VR-018 classified as: ['AdequateVoltage']
```

Figure 9: Reasoning performance with 40,000 readings

4.4 Discussion

The advantages of OntoFreya lie in the automated classification of the values of the power distribution network. After the insertion of the rules into the ontology, the reasoner quickly performs the inferences and provides the output class results. Another advantage is the proposal of an ontology oriented to the power distribution domain. Specifying a domain allows for a better representation of entities, showing possible status or conditions that these entities are. The generic modeling of the OntoFreya ontology allowed changes in the reference value and a new round of inferences, as shown in Scenarios 1 and 2.

The most relevant information added to the ontology are the date and hour of an energy reading, the temperature, and the humidity of these entities. The weather information is relevant since the power distribution network is widespread. This way, the contexts could change if they are far from each other. Since there is a specific class for context data, this information type can scale according to the network needs. This context data can also use information from the Internet of Things sensors or devices installed on each equipment.

The scenarios used to validate the ontology show that not only a single instance can present a valid output, but the SPARQL query can also retrieve a batch of readings that match a specific rule or filter. For example, if a specific equipment is not performing well, specialists can query the search for the hour of the day when the equipment presents this behavior. Alternatively, the specialists can query a search with the temperature and humidity to show how these phenomena affect an entity in the domain.

However, OntoFreya initially presented limitations when executed within the Protégé environment, which restricted the number of readings that could be processed and inferred due to performance constraints. To overcome this issue, a development dedicated Python-based implementation using the OwlReady2 library, allowing the ontology to handle large volumes of data. This solution mitigates the scalability limitation by enabling dynamic instance creation and rapid reasoning execution, making OntoFreya capable of processing thousands of readings in just a few seconds. This development represents an important step toward deploying the ontology in real-time and large-scale power distribution environments. Table 4 presents a comparative overview of OntoFreya and traditional monitoring approaches, such as SCADA-based systems. Unlike conventional methods that rely on static, threshold-based rules and limited contextual awareness, OntoFreya applies semantic reasoning to interpret electrical readings through a structured ontology. Its knowledge-based nature allows for enhanced flexibility, reusability, and context-aware inference. OntoFreya can be expanded with new rules, shared across systems, and integrated with external data sources, making it a scalable and future-ready solution for intelligent monitoring in power distribution networks.

Aspect	**Traditional Methods (e.g., SCADA)**	**OntoFreya Ontology**
Classification Approach	Static thresholds and alerts	Semantic reasoning based on formal rules and domain knowledge
Context Awareness	Limited or none	High — supports time, weather, operational context, etc.
Flexibility	Rigid and hardcoded logic	Easily adaptable and extendable with new rules and classes
Reusability	Usually system-specific and closed	Ontology can be reused across systems and shared openly
Scalability	May require custom adaptation for new equipment or logic	Generic structure allows adaptation to various networks and configurations
Expert Dependence	Requires expert intervention for interpretation and tuning	Automates inference after expert-defined rules are implemented
Evaluation Metrics	Based on alerts or thresholds (e.g., alarms triggered)	Deterministic reasoning; traditional ML metrics like F1-score do not apply

Table 4: Comparison between Ontofreya and Traditional Monitoring Methods

Experts from Certaja and CEEE power utilities validated OntoFreya's classification rules, confirming alignment with real-world operational conditions and regulatory compliance. The ontology-based classification approach enables automated reasoning and supports adaptable inference rules, offering flexibility across different power distribution networks. However, the Protégé environment limited the number of readings that OntoFreya could process efficiently. To address this constraint, the implementation with OwlReady2 allowed the system to manage significantly larger datasets, demonstrating its suitability for real-time applications. These enhancements strengthen OntoFreya's role as a decision-support tool, supporting proactive monitoring and classification to help specialists anticipate and resolve network issues.

However, ensuring accurate classification remains a challenge, particularly in scenarios where measured values fluctuate near decision thresholds, leading to potential misclassification risks. To address this, OntoFreya incorporates configurable hysteresis margins, allowing for adaptive adjustments based on operational conditions. Rather than relying on strict, fixed thresholds, the ontology defines tolerance bands to help reduce unnecessary alerts and prevent classification oscillations when values hover around a boundary. For instance, instead of applying a rigid 0.90 pu threshold for critical current classification, a flexible range (e.g., 0.89–0.91 pu) provides greater tolerance and reduces unnecessary alerts. This approach enhances classification stability, ensuring that temporary or minor variations do not trigger repeated state changes, which could otherwise generate misleading alarms or require unnecessary interventions. OntoFreya operates using deterministic, rule-based logic derived from regulatory standards and expert-defined parameters. As a result, its classifications are not probabilistic outcomes but definitive conclusions based on established criteria. Therefore, traditional evaluation metrics such as F1-score, accuracy, or recall — commonly applied to probabilistic machine learning models — are not applicable in this context. Instead, the ontology's correctness is validated through expert review, consistency checks, and its ability to consistently apply domain rules across large datasets. The ability to adjust hysteresis margins and rely on deterministic classification rules allows OntoFreya to be more resilient in real-world scenarios, improving its reliability for power utility monitoring and decision support systems.

Additionally, OntoFreya was developed as part of a research project partially funded by the CEEE power utility company, which provided financial support and real-world operational data for this study. As part of this collaboration, all codes, results, and broader findings from this research were made available to the company for internal use and future implementation. While OntoFreya has been validated with real-world data, the specifics of its industry integration remain confidential due to privacy agreements with the utility company. However, the company possesses the necessary artifacts and documentation to adopt OntoFreya according to its operational requirements.

While both OntoFreya and domain experts apply the same regulatory classification logic, the primary distinction lies in scalability and inferential scope. Experts may require several hours to review and classify hundreds of readings manually, whereas OntoFreya can process thousands in seconds. Furthermore, the semantic structure of the ontology enables higher-level inferences that go beyond individual classifications. For instance, OntoFreya can detect recurring patterns such as voltage drops coinciding with high humidity levels—correlations that may be overlooked in manual inspections.

Such context-aware reasoning represents a key advantage of ontology-based approaches and remains a direction for future investigation.

Finally, the rules inserted in the ontology follow the guidelines of a regulatory agency (ANEEL) or strategic limits from the utility company. The generic nature of OntoFreya allows the use in any network, only converting the network's rules to semantic rules. The search and indications of problems through the inferences can alert the specialists to act proactively in the network equipment. This action can reduce problems that, if not addressed, can generate fines from regulatory agencies. This behavior is typical of a smart grid, acting proactively to anticipate problems that could cause monetary or security damage to the network.

5 Conclusion

OntoFreya classifies and infers data from distribution network readings such as current, voltage, and contextual information. The ontology is generic since each network has specific classification rules, allowing new relationships between terms as necessary. By leveraging a reasoner with axioms and rules based on OWL, OntoFreya enables precise and automatic inferences, facilitating advanced queries based on real-world data instances. The dataset used for validation consists of actual electrical energy readings provided by a partner company, ensuring practical applicability.

This study confirmed the potential of ontologies in electrical engineering as an efficient tool for energy reading classification, which can later be integrated into an Information System for decision support. Future work includes translating the ontology into another programming language to develop a microservice capable of supporting real-time inference for electrical readings, providing insights to operators and engineers responsible for monitoring distribution networks.

Additionally, with the migration to OwlReady2, OntoFreya can now handle significantly larger datasets efficiently, overcoming the limitations of traditional ontology tools like Protégé. This scalability opens opportunities for integrating predictive analytics, allowing OntoFreya to forecast potential grid failures and detect anomalies beyond predefined threshold classifications. Such enhancements would further strengthen its role as a real-time decision support tool in power distribution networks.

Future work will include the development of a microservices-based architecture in which OntoFreya will function as a module within a broader computational system for power distribution monitoring and decision support. This modular design will enhance scalability, support interoperability with monitoring systems, and improve real-time processing capabilities. Structuring OntoFreya as a standalone yet integrable component will enable deployment across diverse power utility environments and simplify future extensions and refinements. This architectural development will advance OntoFreya toward practical adoption within complex power distribution infrastructures. Additionally, future research may explore the design of a broader evaluation framework focused not only on classification outcomes but also on higher-level inferences, pattern discovery, and temporal relationships that may emerge through semantic reasoning.

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References

[ANEEL, 2016] ANEEL (2016). Rules and procedures in power distribution (prodist).

[Aranda, 2024] Aranda, J. A. S. (2024). *OntoFreya: A Power Distribution Ontology for Electric Metrics Classification*. PhD thesis, University of Vale do Rio dos Sinos (UNISINOS).

[Aranda et al., 2021] Aranda, J. A. S., Bavaresco, R. S., de Carvalho, J. V., Yamin, A. C., Tavares, M. C., and Barbosa, J. L. V. (2021). A computational model for adaptive recording of vital signs through context histories. *Journal of Ambient Intelligence and Humanized Computing (2021)*.

[Aranda et al., 2019] Aranda, J. A. S., Dias, L. P. S., Barbosa, J. L. V., de Carvalho, J. V., da Rosa Tavares, J. E., and Tavares, M. C. (2019). Collection and analysis of physiological data in smart environments: a systematic mapping. *(Journal of Ambient Intelligence and Humanized Computing*, 11(7):2883–2897.

[Aranda et al., 2022] Aranda, J. A. S., dos Santos Costa, R., de Vargas, V. W., da Silva Pereira, P. R., Barbosa, J. L. V., and Vianna, M. P. (2022). Context-aware edge computing and internet of things in smart grids: A systematic mapping study. *Computers and Electrical Engineering*, 99:107826.

[Attia et al., 2025] Attia, M. et al. (2025). Study of power quality issues without and with microgrid in egypt. *Scientific Reports*, 15:2297.

[Barbosa et al., 2018] Barbosa, J., Tavares, J., Cardoso, I., Alves, B., and Martini, B. (2018). Trailcare: An indoor and outdoor context-aware system to assist wheelchair users. *International Journal of Human-Computer Studies*, 116:1 – 14.

[Barbosa, 2015] Barbosa, J. L. V. (2015). Ubiquitous computing: Applications and research opportunities. In *2015 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, pages 1–8.

[Bavaresco et al., 2024] Bavaresco, R., Ren, Y., Barbosa, J., and Li, G. (2024). An ontologybased framework for worker's health reasoning enabled by machine learning. *Computers and Industrial Engineering*, 193:110310.

[Chong et al., 2020] Chong, A. T. Y., Mahmoud, M. A., Lim, F.-C., and Kasim, H. (2020). Description for smart grid: Towards the ontological approach. In *2020 8th International Conference on Information Technology and Multimedia (ICIMU)*. IEEE.

[dos Santos Costa et al., 2023] dos Santos Costa, R., Aranda, J. A. S., de Vargas, V. W., da Silva Pereira, P. R., Luis Victoria Barbosa, J., and Vianna, M. P. (2023). Data analysis techniques applied to distribution systems: A systematic mapping study. *Electric Power Components and Systems*, 51(5):452–467.

[dos Santos Costa et al., 2022] dos Santos Costa, R., da Silva Pereira, P. R., Madruga, E. P., Aranda, J. A. S., and Barbosa, J. L. V. (2022). A hybrid model for investment prioritization and performance analysis in electrical power distribution systems. *Journal of Control, Automation and Electrical Systems*, 34(2):420–428.

[EPRI, 2025] EPRI (2025). Der integration on radial distribution systems. Technical report, EPRI.

[Fernandez-López et al., 1997] Fernandez-López, M., Gómez-Pérez, A., and Juristo, N. (1997). Methontology: From ontological art towards ontological engineering. In *AAAI Conference on Artificial Intelligence*.

[Helfer et al., 2025] Helfer, G. A., da Costa, A. B., and Barbosa, J. L. V. (2025). Soilbr-onto: An ontology for soil fertility management and classification in brazil. *Applied Ontology*, 0(0):15705838251315571.

[IEC, 2009] IEC (2009). *IEC 60038:2009 Standard Voltages*. Geneva, Switzerland. Available at: https://webstore.iec.ch/publication/153.

[IEEE, 2018] IEEE (2018). IEEE Std 1547-2018: Standard for interconnection and interoperability of distributed energy resources with associated electric power systems interfaces. DOI:
https://doi.org/10.1109/IEEESTD.2018.8332112.

[Larentis et al., 2021] Larentis, A. V., de Azevedo Neto, E. G., Barbosa, J. L. V., Barbosa, D. N. F., Leithardt, V. R. Q., and Correia, S. D. (2021). Ontology-based reasoning for educational assistance in noncommunicable chronic diseases. *Computers*, 10(10):128.

[Lee et al., 2022] Lee, C. C., Yuan, Z., and Wang, Q. (2022). How does information and communication technology affect energy security? international evidence. *Energy Economics*, 109:105969.

[Leighton et al., 2021] Leighton, K., Kardong-Edgren, S., Schneidereith, T., and Foisy-Doll, C. (2021). Using social media and snowball sampling as an alternative recruitment strategy for research. *Clinical Simulation in Nursing*, 55:37–42.

[Li et al., 2019] Li, H., Armiento, R., and Lambrix, P. (2019). A method for extending ontologies with application to the materials science domain. *Data Science Journal (2019)*, 18.

[Nti et al., 2021] Nti, I. K., Adekoya, A. F., Weyori, B. A., and Nyarko-Boateng, O. (2021). Applications of artificial intelligence in engineering and manufacturing: a systematic review. *Journal of Intelligent Manufacturing (2021)*.

[Pradeep et al., 2021] Pradeep, P., Krishnamoorthy, S., and Vasilakos, A. V. (2021). A holistic approach to a context-aware IoT ecosystem with adaptive ubiquitous middleware. *Pervasive and Mobile Computing*, 72:101342.

[Salameh et al., 2019] Salameh, K., Chbeir, R., and Camblong, H. (2019). SSG: An ontologybased information model for smart grids. In *Lecture Notes in Computer Science*, pages 94–124. Springer Berlin Heidelberg.

[Schachinger et al., 2016] Schachinger, D., Kastner, W., and Gaida, S. (2016). Ontology-based abstraction layer for smart grid interaction in building energy management systems. In *2016 IEEE International Energy Conference (ENERGYCON)*. IEEE.

[Smirnov et al., 2021] Smirnov, A., Levashova, T., Ponomarev, A., and Shilov, N. (2021). Methodology for multi-aspect ontology development. In *Lecture Notes in Business Information Processing*, pages 97–109. Springer International Publishing.

[Zainab et al., 2021] Zainab, A., Ghrayeb, A., Syed, D., Abu-Rub, H., Refaat, S. S., and Bouhali, O. (2021). Big data management in smart grids: Technologies and challenges. *IEEE Access*, 9:73046–73059.

[Zanabria et al., 2019] Zanabria, C., Andren, F. P., Strasser, T. I., and Kastner, W. (2019). A model-driven and ontology-based engineering approach for smart grid automation applications. In *IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society*. IEEE.

[Zheng et al., 2021] Zheng, J., Okamura, H., Pang, T., and Dohi, T. (2021). Availability importance measures of components in smart electric power grid systems. *Reliability Engineering System Safety*, 205:107164.