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Proposing an Ontology Model for Planning Photovoltaic Systems

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Abstract: The performance of a photovoltaic (PV) system is negatively affected when operating under shading conditions. Maximum power point tracking (MPPT) systems are used to overcome this hurdle. Designing an efficient MPPT-based controller requires knowledge about power conversion in PV systems. However, it is difficult for nontechnical solar energy consumers to define different parameters of the controller and deal with distinct sources of data related to the planning. Semantic Web technologies enable us to improve knowledge representation, sharing, and reusing of relevant information generated by various sources. In this work, we propose a knowledge-based model representing key concepts associated with an MPPT-based controller. The model is featured with Semantic Web Rule Language (SWRL), allowing the system planner to extract information about power reductions caused by snow and several airborne particles. The proposed ontology, named MPPT-On, is validated through a case study designed by the System Advisor Model (SAM). It acts as a decision support system and facilitate the process of planning PV projects for non-technical practitioners. Moreover, the presented rule-based system can be reused and shared among the solar energy community to adjust the power estimations reported by PV planning tools especially for snowy months and polluted environments.

Keywords: knowledge-based model; ontology; PSC; rule-based model; PV shading; snow-covered module

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1. Introduction

Since 25 years ago, solar energy has become one of the main contributors among other forms of renewable energy resources [1]. A photovoltaic (PV) system can be operated conveniently, requiring little maintenance. Using current-voltage (*I-V*) tracing approaches, performances of a PV module or even solar panels of a utility-size PV system, a power plant can be measured by system operators [2]. These online diagnosis and cost-efficient techniques provide accurate data needed for effectively operating a PV system power plant [3]. In Canada, the use of the solar PV system has been growing from 16.7 megawatts in 2005 to 3040 megawatts in 2018 [4]. The convenience of installing a PV system has motivated residential and commercial users to consider it as an important source of energy for their needs. It means that consumers with minimum or basic knowledge about a solar panel must deal with the process of the PV system planning. However, the planning of an efficient system requires an expert's knowledge, especially when modules operate under shading conditions [5]. PV shadings are caused due to various ambient terms. Adjacent buildings, trees, clouds, pollution, dust, and snow considerably reduce energy generations of a solar panel. The performance of a solar panel is degraded when operating under shading conditions. The online inspection of PV modules allows us to identify the shading status of multiple different panels at a time [6]. In the case of shading, a maximum power point tracking (MPPT) method, it aids the system to perform in its optimal operation. An MPPT-based control system implements the algorithm and controls the produced energy.

The importance of improving power efficiency in the solar sector market has motivated researchers with different scientific backgrounds to study MPPT approaches. There exist numerous published papers and scientific contributions linked to the subject of tracking a maximum power point. Researchers' diverse backgrounds [7] and their non-technical points of view have produced an overwhelming amount of information in this topic [8,9]. It is difficult to evaluate their results and practically utilize the proposed methods since dissimilar terminologies and research interests are applied in their works. Moreover, the rule of environmental factors and external parameters have been neglected even in most literature reviews, for instance in [7,10,11]. Consequently, many research studies provide algorithms, techniques, and hybrid methods which are nonpractical solutions in the context of power conversion. Choosing an appropriate algorithm based on the application and determining its parameters and initial values are among some of the problems concerning PV system design [8]. For instance, control parameters of an MPPT-based control system can be adjusted to change the functionality of an MPPT algorithm and its efficiency [12]. In addition, the problem concerning ambient conditions is more complex, since they involve meteorological data and environmental factors requiring different knowledge domains.

During recent years, developing conceptual frameworks has grown significantly, allowing researchers to reuse and share information within interested communities [13]. Modelling disparate conceptual data from different domains implies using artificial intelligence, that involves semantics and computer processable languages [8,14]. Semantic Web technologies offer software languages for representing knowledge-based models. In this work, we propose an ontology model representing the semantics and information required for planning PV systems to operate efficiently in various ambient conditions. The presented ontology aids to define required parameters for an MPPT-based controller. It provides Semantic Web Rule Language (SWRL) guidelines for extracting information about power degradations due to snow-covered modules and several airborne particles. The designed ontology, named MPPT-On, is developed using reasoning and queries. The evaluation of the proposed ontology is performed using a case study. As the most reliable PV planning software [15], which is broadly used by PV practitioners and researchers, the System Advisor Model (SAM) is employed for planning the PV project. We apply the applicable rules to adjust the hourly power estimations provided by SAM for snowy months, considering environmental factors as well. Then, we compare power estimations reported by SAM and MPPT-On with the actual power productions collected onsite for the case study. The results indicate that the application of the proposed ontology helps to estimate more accurate output results for months expecting snowfalls. Furthermore, the proposed model offers technical recommendations and design-related parameters associated with an MPPT-based controller.

This paper is structured as follows: the next section aims to demonstrate the impacts of shading conditions on the *P-V* and *I-V* characteristics of a partially shaded solar arrays using a MATLAB simulation. In Section 3, the application of an MPPT method in the control system is described briefly. MPPT classifications and algorithms, the key elements of the proposed model, are reviewed in this portion as well. The concept of the Semantic Web and the application of ontology in the energy sector are introduced in Section 4. We design the proposed ontology using Ontology Development 101 in Protégé. Then, ontology reasoning and the rule-based system are developed, considering shading conditions. The effects of several airborne particles, snow, and cloud on PV performances are presented at the end of this section. Moreover, power degradations related to different panel inclinations are outlined. The proposed ontology is evaluated in Section 5 by using a case study. We design the PV system and plan the case study employing SAM. In Section 5.1, the hourly power estimations calculated by SAM are manipulated using the rules defined in the proposed model. The results of the hourly power estimations reported by SAM are compared with the application of MPPT-On in Section 6. We use the real data of power productions gathered onsite as the comparison for our analysis. Finally, a conclusion is presented in Section 7.

2. Shading Conditions

2.1. PV Cell Model

An electrical circuit model of a PV system enables us to predict variations of *I-V* and *PV* curves to the ambient conditions and climate factors. Using an appropriate electrical circuit model and an estimation of its parameters are crucial to envisage PV performances and the energy yield. The most important element of a solar module is the PV cell [16]. MATLAB/Simulink are widely used in the domain to simulate PV arrays. In the software, the cell behaves as a simple diode p–n junction representing two layers of semiconductor material. The characteristic of the diode is explained by the following equation:

$$I_D = I_0[\exp\,(qV/akT) - 1], \tag{1}$$

This part of the equation was modified by adding resistances R_S and R_P in the single diode R_S-model and single diode R_P-model. In MATLAB, the single diode R_P-model was employed [17]. Other PV models either neglect important physical characteristics of a PV cell, such as the ideal model and single diode R_S-model, or present more variables requiring extra simulation time [18]. Equation (2) describes the *I-V* relationship in a single diode R_P-model.

$$I = I_{PV} - I_0[exp\,(q\,(V + IR_s)/akT) - 1] - (V + IR_s)/R_p, \tag{2}$$

where I_{PV} is the PV current and has a direct relationship with sun intensity and temperature changes. The saturation current (I_0) depends on temperature differences, a is the ideality (or quality) factor of the diode, q is a constant amount ($-1.6021764 \times 10^{-19}$) representing an electron's charge, k is Boltzmann's constant ($-1.380653 \times 10^{-23}$ J/K), T (°K) is the absolute temperature of the *p–n* junction, and R_S and R_P are the series and parallel equivalent resistances of the solar panel, respectively [19].

2.2. Impacts of Shading Conditions on PV Curves: The Simulation

Practically, a PV system is built in a series-parallel configuration to form an array at the desired output voltage and current [20]. To demonstrate the effect of shading conditions on PV performances, we considered uniform shading conditions (USCs). We demonstrated performances of solar panels operating under USCs using MATLAB Simulation Toolbox. Table 1 presents the module data chosen in the simulation.

Table 1. SunPower SPR-X20-250-BLK module data.

Parameter	Value
Maximum power (P_{MAX})	213.15 (W)
Open circuit voltage (V_{OC})	36.3 (V)
Voltage at MPP (V_{MPP})	29 (V)
Cells per module	60
Short-circuit current (I_{SC})	7.84 (A)
Current at MPP (I_{MPP})	7.35 (A)

A solar panel generates less power and current when it experiences less irradiance. Solar panels can be uniformly shaded by various environmental and climate-related factors, including dust, snow, and airborne particles caused by pollutions. The severity of shadings is influenced by different factors, including the bypass diode placement, type of the particle, its property, PV type, glazing, the tilt angle, and climate conditions of the site [21,22]. We included these concepts in the proposed knowledge-based model to represent their relationships with PV shadings, though their impacts on PV performances have not been neither investigated nor simulated. In fact, ambient factors might affect the duration of the shading, but their impacts on uniformly or partially shading conditions of a module remain the same.

We apply the following PV configuration (Figure 1) to demonstrate characteristics of the module when operating under USCs. Figure 2 can be realized as the *P-V* and *I-V* curves of snow-covered SunPower SPR-X20-250-BLK modules. While one module receives the full irradiance, the other three perform in different irradiances of 500 (W/m^2), 100 (W/m^2), and 300 (W/m^2). Unlike the USC, the *P-V* and *I-V* curves portray two local points and one global maximum concerning the PSC.

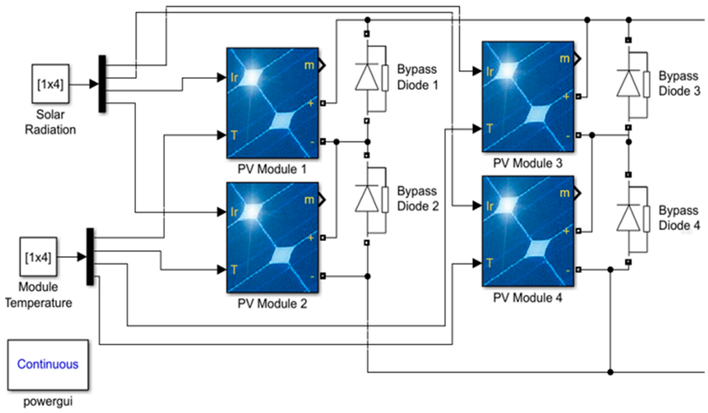

Figure 1. The PV configuration used in MATLAB (Source: Authors).

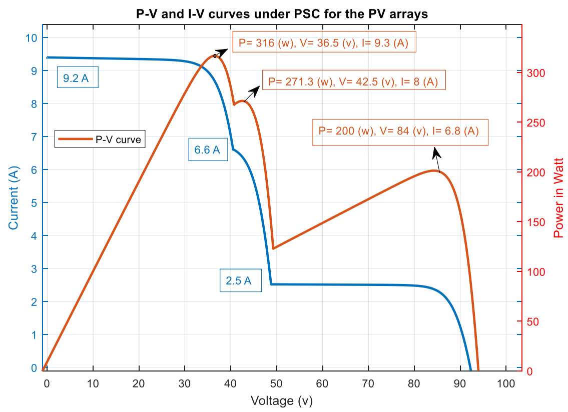

Figure 2. The *P-V* and *I-V* characteristics of the partially shaded PV arrays (Source: Authors).

Chemical, biological, and electro-statistic effects of various airborne articles also affect PV performances and severity of shading in long term operations [23]. Nevertheless, snowfall and dust are the main sources of solar power degradations in most cases [21]. Snowfall in cold climates is considered as the major reason for PV performance reductions [21,22]. Solar modules receive less sunlight when the depth of snow is increased. In a full shading situation, there is no irradiance reaching the surface of a module and will result in zero power production.

3. MPPT Methods

3.1. The Application of an MPPT-Based Control System

PV systems can be designed stand-alone or grid-connected depending on the application. Stand-alone systems normally deliver power to a single load or off-grid network of electric loads. Grid-connected PV systems deliver power to the grid and interact with the power network [24]. The overall topology of a PV system containing an MPPT-based controller is shown in Figure 3. Practically, in a usual application, the controller provides appropriate duty cycles to the DC–DC buck converter. The MPPT algorithm modulates the duty cycle for the converter and enables the PV system to perform in its maximum efficiency. In fact, an MPPT algorithm tracks the global point on the *P-V* curve allowing the system to perform in its optimal operation. The controller implements based on the data received from voltage and current sensors. It provides reference voltages or reference currents needed for the PV module. Then, according to these references, the pulse width modulation (PWM) generator delivers a suitable duty cycle to the converter. The application of an MPPT-based controller is to maximize $P_{PV}(d)$ subjected to $d_{min} \leq d \leq d_{max}$, where d_{min} and d_{max} are the lower and upper bounds of the duty cycle of 10% and 90%, respectively [25].

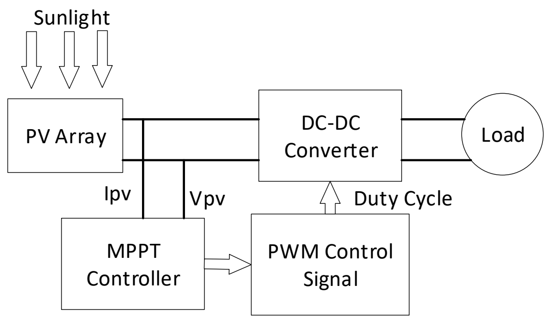

Figure 3. Centralized or field MPPT architecture (Source: Authors; architecture adapted from [26]).

3.2. MPPTs: A Survey

Classifications of existing methods representing functionalities of MPPT algorithms are widely distinctive. These perceptions mainly focus on characteristics of methods, including application, optimization technique, cost, parameters used, efficiency, tuning parameters, complexity, and convergence [27]. Ultimately, the most common clustering can be defined as: (I) conventional or classical methods, (II) modern or soft computing methods, (III) hybrid methods, and (IV) power electronics (PE) methods.

Major conventional methods are known as: perturbation and observation (P&O), incremental conductance (IC), hill climbing (HC), fractional short-circuit current, fractional open-circuit voltage, ripple correlation control, three-point weighted average, extremum seeking (ES) control, sliding mode control, load current/voltage maximization, bisection search and β-method [8,9,12]. In most cases, when a PV module is involved in the system, these methods are capable of tracking maximum points even in varying ambient conditions. However, they may be trapped in local points and detect one of the local points as the global point when PSC occurs. The P&O algorithm describes the logic behind classical techniques. They attempt to add a small portion to the voltage or current of a PV system to previous values in order to find the maximum point. Conventional methods offer convenience and simplicity [28]. Furthermore, they provide less efficiency and convergence speed compared to soft computing algorithms [26]. Yet, they play important roles in engineering applications based on their simplicity, flexibility, gradient-free mechanism, and capability of searching global optima in normal cases [29,30].

Soft computing methods can be categorized into artificial intelligence (AI) and meta-heuristic optimization [31]. AI-based techniques comprise the artificial neural network (ANN), fuzzy logic (FL), and the adaptive neuro-fuzzy inference system (ANFIS) [30]. Meta-heuristic approaches can be categorized into two subdivisions, the evolutionary algorithm (EA) and the population-based or swarm intelligence (SI) methods. SI techniques mimic evolution and social behavior of creatures in nature [30]. EA-based algorithms are inspired by the evolutionary concepts of nature. Evolving an initial random solution performs the optimization by creating a new population by the combination and mutation of the previous generation. One of the most practiced EAs employed in PV systems is differential evolution (DE) [32,33]. SI-based techniques are mostly inspired from natural colonies, flocks, herds, and schools. Aside from the context of MPPT, Mirjalili et al. introduce several swarm-based algorithms: the Bat-inspired Algorithm (BA), Marriage in Honey Bees Algorithm

(MBO), Wasp Swarm Algorithm, Artificial Fish-Swarm Algorithm, Monkey Search, Cuckoo Search (CS), Fruit fly Optimization Algorithm (FOA), Krill Herd (KH), Dolphin Partner Optimization (DPO), Bee Collecting Pollen Algorithm, and Firefly Algorithm [29]. In a recent work [34], Harris hawks optimization was developed to deal with the nonlinearity of PV curves under shading in real-world applications.

Researchers have been improving conventional and soft-computing approaches by hybridizing them. Modifying a method or combining two approaches from different classifications can improve the functionality of the original algorithm [9]. Hence, the combination of any method in each category with another approach can result in developing a hybrid method. However, due to the complexity of their algorithms, applications of these methods in the real world are questionable. In our classification, we categorized any improved and modified MPPTs in the cluster of hybrid methods. For instance, the Slime mold optimization (SMO) and improved salp swarm optimization algorithm (ISSA) introduced in an article [35], were considered as hybrid methods in the classification.

Utilizing the hardware and technical features of power electronics components is the main aspect behind PE-based methods. In a previous work [36], we studied these methods and highlighted the important role of microcontroller-based (MCU-based) MPPT techniques. Unlike numerous studies concentrating on developing redundant soft computing MPPT algorithms, major elements of a PV system and its architecture play main parts in improving PV performances concerning shading conditions [26,37]. The three major PE-based methods are named as: the bypass diode method, the PE equalizer, and a method which is known with the acronym TEODI [38,39]. In fact, advanced features of nowadays' MCUs, such as temperature and irradiance sensors along with Wi-Fi connectivity, can be developed in the context of power conversion.

4. Knowledge-Based Models

4.1. An Overview of Ontology

The Semantic Web, introduced by Berners-Lee [40], improves unstructured and/or semi-structured Web pages and documents into a structured, well-defined and meaningful content of Web data. The need for a common framework that enables data sharing among a community has been the motivation behind the notion of the Semantic Web [41]. Ontology enables semantic relations among represented entities [42]. An ontology can be interpreted as formally describing a domain of interest through an abstract model [43]. In this manner, the community of a certain domain can reuse and develop the shared knowledge constructed with similar terminology. In fact, ontologies are agreements about sharing conceptualizations, containing conceptual frameworks for modeling knowledge and the representation of a specific domain [44]. They provide a hierarchy form of specified concepts in the form of classes [45]. An ontology model can: (I) deal with large volumes of information and data, (II) share knowledge and (III) incorporate the relevant domain concepts and their associated relations [46].

Ontologies are formed by utilizing explicit formal languages [47]. Among many ontology languages, the Web Ontology Language (OWL) is the most popular. It has been developed by researchers to handle complex semantics. It can handle numerous classifications, properties, and constraints in various applications [48]. Ontology editors have emerged in recent years to assist practitioners. We used Protégé to design and develop the proposed ontology in addition to implementing SWRL reasoners. As defined in [49], "Protégé is a free, open-source platform that provides a growing user community with a suite of tools to construct domain models and knowledge-based applications with ontologies". It is an ontology development environment that allows to create, upload, modify, and share ontologies. It supports OWL 2 Web Ontology Language and description logic reasoners such as Hermit and Pellet [49].

4.2. The Application of the Semantic Web in Energy Management

The notion of human and machine interaction establishes a unique collaboration between semantics and the domain of energy management and the solar energy sector. In a related paper [50], an ontology is presented providing recommendations to increase efficiency for appliances. The presented ontology unfolds knowledge of residential appliances and the energy consumed. In this way, related factors influencing the energy consumption can be analyzed and managed. Moreover, the ontology incorporates household information and family members' behavior using appliances. In a relevant work [51], the goal of the Semantic Web model (DogOnt) is to provide a variety of options available for generating energy, depending on the building, the number of living residences, operating devices, and appliances. In a home energy management system (HEMS), rules are applied to create energy management strategies to reduce and optimize consumption [52]. In the sector of urban energy systems (UES), a knowledge-based platform is introduced for modelling urban energy systems [53,54]. The model characterizes components of the UES domain, including object classes representing the main parameters of an urban energy system [53]. It consists of resources, infrastructure, and processes as the main categories of classes. Related to the solar energy domain, a knowledge-based system is presented assisting decision makers by recommending appropriate PV system configurations [55]. In another paper [45], an ontology model is proposed for optimizing domestic solar hot water system selection. The proposed tool assists non-technical consumers with their needs to choose components of the solar hot water system and the installation costs in the form of an ontology model. The system configurations are computed based on various specific parameters, such as number of occupants, daily hot water requirements and house location [45].

4.3. Defining the OWL Model Assertion Axioms and Their Relationships

Defining the classes, their attributes, and relationships allowed us to design the ontology model using Protégé. We used UML diagrams to demonstrate classes, attributes, and their relationships. The data type, the visibility, and the name associated with each attribute describe several features of a class or a subclass as well as any instance or variable in the class. The defined classes, attributes, and their relationships were used later for designing the ontology and reasoning with further considerations. Figure 4 depicts the UML diagram of some of the most important concepts that affect the planning of a PV project and their relationships. The figure helps to define the resource description framework (RDF) leading to data properties, object properties, data values, data type, and restrictions about every concept. For brevity, the super-classes, and a few data properties and object properties are shown here.

4.4. Designing the Proposed Ontology

In this step, we identified semantics and concepts related to MPPT methods in the PV domain. There are several ontology methodologies for developing an ontology, including Methontology [56], On-To-Knowledge [14], NeOn [57], and the Horrocks Ontology Development Method [58]. Whereas these methodologies have been utilized in several knowledge-based domains, we need to apply a method that offers convenience technologies working with many software environments. Ontology Development 101 is a well-known and most practiced methodology for developing ontologies [59]. The concept of Ontology Development 101 was adopted for developing the proposed ontology. In the methodology, four main activities need to be defined [59]: (1) different terms in the domain and relations among them, (2) concepts (classes) in the domain, (3) hierarchy arrangement of the concepts (subclasses and classes relationships), and (4) constraints, values, and properties values. This methodology presents technologies to build an ontology from the starting point. We used Protégé and its plug-ins to apply the OWL language and SWRL reasoning.

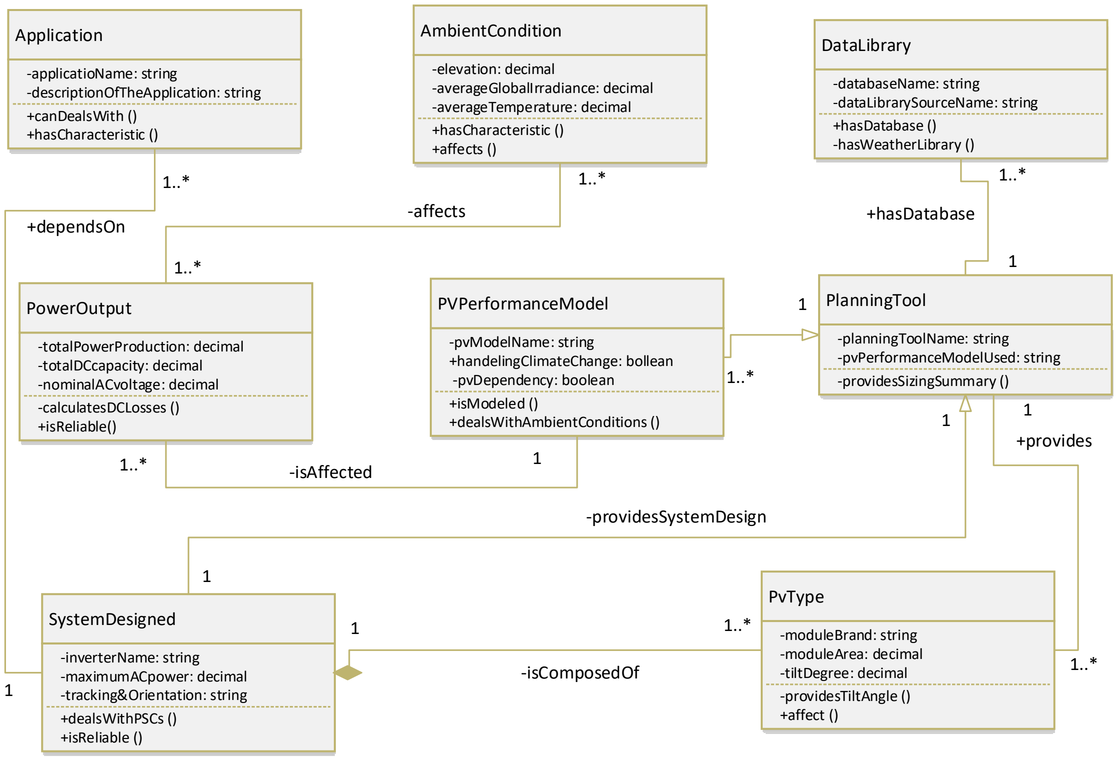

Figure 4. UML diagram of the key concepts associated with the PV planning.

There were key concepts used in Protégé, including individuals, classes, and properties. Individuals, also known as instances, can be referred to as being "instances of classes." Classes contain all the individuals that are categorized in a domain of interest. Classes may be organized into a superclass or subclass hierarchy, which is also known as a taxonomy. A class represents a concept in the domain or a collection of elements with similar properties. Properties are binary relations on individuals connecting two individuals together. Properties describe attributes of instances of the class and relations to other instances. Object properties are relationships between two individuals. Data properties describe relationships between individuals and data values. Annotation properties can be used to add information (metadata—data about data) to classes, individuals, and object/data properties. We implemented the following steps to construct our ontology:

1. Creating the class hierarchy.
2. Defining the OWL properties: defining their type (functional, transitive, symmetric, reflexive, etc.) and defining their domain/range as per need.
3. Describing and defining the classes created for example restrictions (axioms).
4. Invoking the reasoner, checking the consistency of the ontology, and creating the inferred view.
5. Creating certain individuals by assigning certain OWL properties.
6. Executing the reasoner and checking it.

Figure 5 illustrates the graphical representation of the proposed model, including super-classes and their relationships. The developed ontology model (MPPT-On) is available and can be viewed and performed in [60]. The next step of developing MPPT-On was to set up SWRL rules and Semantic Query Enhanced Web Rule Language (SQWRL) queries.

4.5. Ontology Reasoning and SWRL Rules

Researchers have developed reasoners to infer the knowledge-based models. The W3C team standardizes the SWRL for expressing different conditions in real applications [40]. SWRL includes a high-level abstract syntax in the sublanguages of OWL [61]. A query language can be used to extract information from OWL ontologies. SQWRL, developed by O'Conner et al., provides a concise, readable, and semantically robust query language for OWL [62]. It provides different and useful operators that support negation as failure, disjunction, counting, and aggregation functionality. An implementation of SQWRL has been developed in the SWRLTab plugin in Protégé. It provides a graphical interface to set, edit, and run SQWRL queries and also provides a Java interface to execute SQWRL queries in Java applications [62]. Rule-based ontologies can establish rules and logics to interpret different contexts, including structured and unstructured data [41]. Unlike if–then rules in programming languages, reasoners have been developed to infer the ontologies. In Protégé, reasoning over the ontology was performed by employing plug-ins, for instance HermiT, Pellet, FaCT++, etc. Pellet provides an extensive support for reasoning with individuals which played an important role in our model [63]. Sirin et al. states that Pellet fulfils most of the latest approaches and optimization techniques provided in the DL literature.

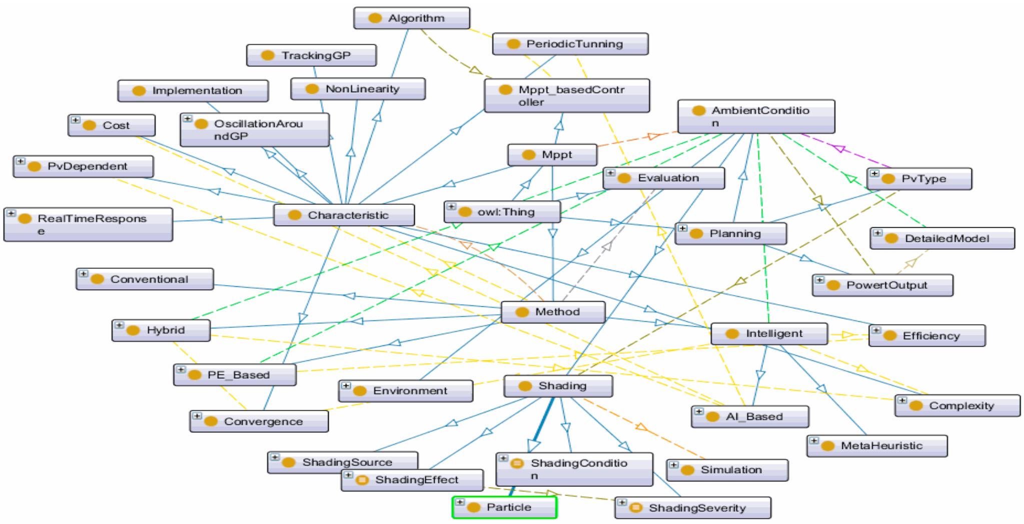

Figure 5. A graphical representation for MPPT characteristics and its classifications.

4.5.1. A Rule-Based System for MPPTs

During the process of identifying class axioms, three areas were detected as the mainstream knowledge sources in the context of MPPTs: (I) the methods, (II) characteristics of the methods, and (III) technical properties of the controller. MPPT methods represent a knowledge based on the algorithms, different techniques, parameters involved, mathematical approaches employed, and related variables. Characteristics of methods present information about criteria and measures that an MPPT approach can be compared with. The third key knowledge area introduces the hardware of the controller. Technical features and physical properties of the control system were embodied in this stream. Figure 6 outlines these data properties from which the SWRL rules were extracted. The prioritized numbers identify the priority of rules. SQWRL queries were defined for MPPTs based on this rule-based framework.

4.5.2. SWRL Rules for Shadings and Tilt Angles

Herein, the goal was to determine rules to make corrections for power estimations reported by the PV planning software overlooking module shadings caused by snowfall and several other environmental factors. Therefore, the factors that were not associated with the climate or environment of the PV site were excluded, including self-shading. However, various sources creating shading for PV systems were defined as classes in the proposed ontology. We set up rules for snow and polluted particles that were the main source of shadings in many cases. These factors and their impacts on module performances are presented in Tables 2 and 3. Table 4 highlights the effect of several inclinations on PV performances. The tilt angle is a fix factor and is irrelevant to ambient conditions.

However, its impact on system performance and the attention received by experts in the PV community encouraged us to include several rules about inclinations. Its influential role in snow shedding and its impact on the duration of snow coverings on solar panels are undeniable. These Tables outline the defined rules determined for the ontology model.

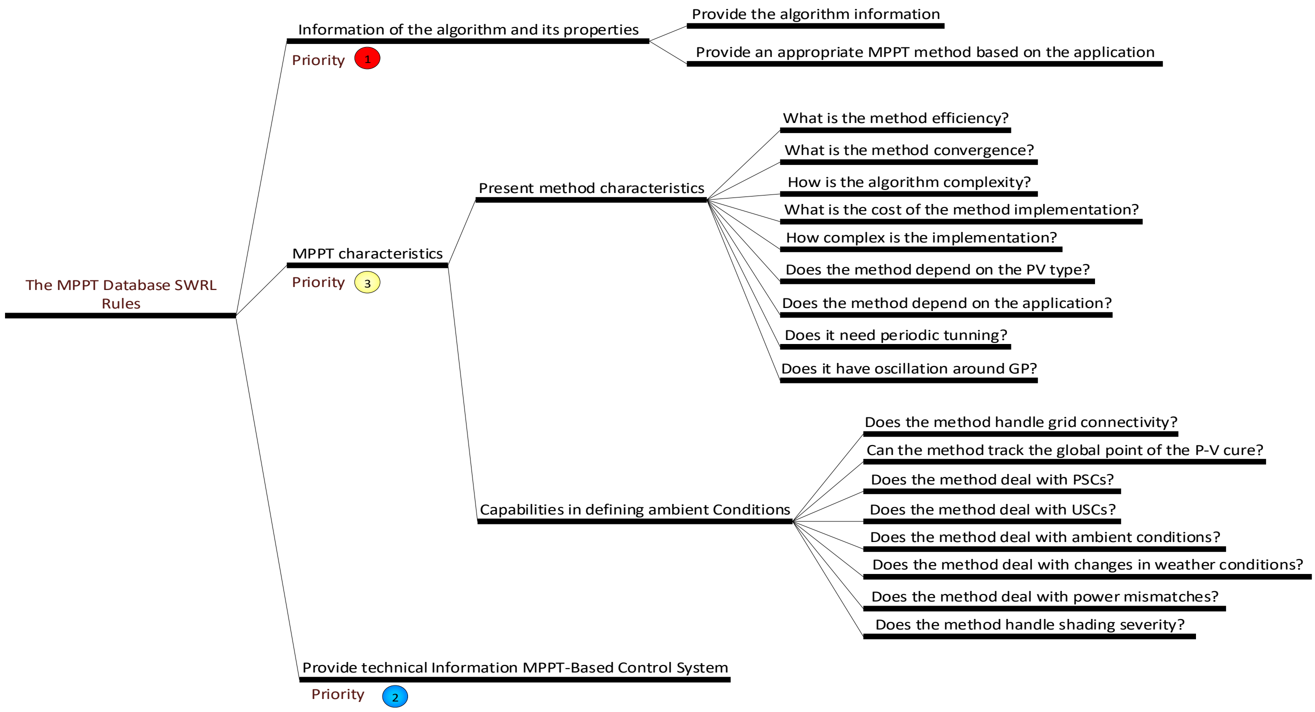

Figure 6. The structure of SWRL rules used for the MPPT database.

Table 2. The effects of airborne particles affecting PV performances.

Particle Type	Effect on PV Performance
Dust and Sand	2–2.5% decrease in power [64]
Airborne Dust	At least 33.5% decrease in efficiency [65]
Cement Dust	80% drop in PV short circuit voltage (deposition of 73 g/m^2) [66]
Dust	6–13% decrease in output power ([67]) Average of 4.4% daily energy loss that could increase to 20% in dry conditions [68] 50% reduction in the power for the panels exposed without cleaning for six months [69] 2.78% daily reduction for silicon solar panels in short circuit current [70] 10% power reduction after 5 weeks of the exposure (UAE) and 10% in module efficiency [71,72] 5–6% decrease in module efficiency [73] 16–29% degradation of energy yield of 7 different PV modules without any cleaning procedure for 18 years [74] 11% reduction in the energy production (5 g/m^2 dust deposition) [75] 15–21% decrease in the short circuit current [76] 2–6% reduction in the open circuit voltage [76] 15–35% degradation for the efficiency [76] About 15% losses with periods without rain [77] 5% or more annual energy losses [78]
Sand	About 4% reduction in PV voltage [79]
Red Soil	About 7% decrease in voltage [79]
Ash	25% PV voltage reduction [79]
Calcium Carbonate	5% reduction in PV voltage [79]
Silica Gel	About 4% reduction in PV voltage [79]

Table 3. Power reductions due to cloud and snow.

Particle Type	Effect on PV Performance
Cloud	77% reduction in power output [80]
Snow	50% lower than evaluated PV energy [81] 0.3–2.7% decrease in annual yield [82] 4.25% yearly energy loss [83] 1.5–5.2% of one year's production [84] Snow depth > 2.54 (CM) cause 45% of daily loss, and < 2.54 (CM) cause 11% daily loss (for 30° module angle) [85] Snow depth > 2.54 (CM) cause 26% of daily loss, and < 2.54 (CM) cause 5% daily loss (for 40° module angle) [85] 1–12% annual energy production losses [86]

Table 4. The effects of inclinations on PV performances affecting the duration of shading, caused by snow-covered modules.

Inclination	Effect on PV Performance
25° tilt angle	Power is 5.6% to 17.3% higher than 6° tilt depending to the site plant [87]
45° tilt angle	17.4% energy loss per month for south-facing panels [88]
23° tilt angle	70% losses in winter months [78]
40° tilt angle	40% reductions in winter months [78]
0° tilt angle	18% losses in generation [78]
24° tilt angle	15% losses (annually estimated) [78]
39° tilt angle	12% losses (annually estimated) [78]
Dual axis	Produce about 30% more electricity than the tilted system [89]
30° tilt angle	Snow depth > 2.54 (CM) cause 45% of daily loss, and < 2.54 (CM) cause 11% daily loss [85]
40° tilt angle	Snow depth > 2.54 (CM) cause 26% of daily loss, and < 2.54 (CM) cause 5% daily loss [85]

We developed these SWRL rules for the proposed ontology using the SQWRL plug-in in Protégé. The following present three rules defined in the SQWRLTab environment for extracting information about (I) the effect of snow depth more than 2.54 (cm) and two different module angles, (II) the effect of a 45° tilt angle on energy loss per month for a south-facing panel, and (III) the effect of dust on the short circuit voltage:

Rule I. *Shading(?s) ^ particleType(?s, "Snow depth more than 2.54 (cm)) ^ powerAdjustmentReport(?s, ?pa) -> sqwrl:select(?s, "Shadings with snow origin for depth more than 2.54 (cm) and two different tilt angles:", ?pa)*

Rule II. *SystemDesigned(?s) ^ tiltDegree(?s, "45° tilt angle") ^ powerAdjustmentReport(?s, ?pa) -> sqwrl:select(?s, "The effect of a system designed with PVs with 45 degree tilt angle on energy loss per month for south facing panel:", ?pa)*

Rule III. *Shading(?s) ^ particleType(?s, "Dust on short circuit current") ^ powerAdjustmentReport(?s, ?pa) -> sqwrl:select(?s, "The effects of dust on the short circuit voltage:", ?pa)*

5. Validation of the Proposed Model

The evaluation of an ontology is as important as developing it. Evaluation can be deemed as an approval for the application of a developed ontology. It indicates how suitable the ontology model is for what it is supposed to be used for. The proposed ontology was semantically validated by a case study that its power generations are publicly available [90]. The measured system performance data for the project are accessible in Excel files for the entire year of 2012. These files include hourly power productions, snow data, and technical features of the PV system.

The case study was a PV system installed in one of the buildings at the National Renewable Energy Laboratory (NREL) in the United States, known as Research Support Facility 2 (RSF 2), in 2011. The system was a 408-kW solar array on the roof of the new A-wing expansion of the RSF located in Golden, Colorado at 39.74° (N), 105.18° (W), with an elevation of 1829 (m). The complete technical description of the case study can be found in [91]. Using the SAM simulation (version 2020.2.29), we designed the PV power generation system choosing the same inverter and module of the actual project in order to compare our simulation and power estimations with the real data gathered from the site. The technical characteristics and the sizing summary of the system designed is presented in Table 5.

Table 5. Sizing summary of the PV system designed for the case study using SAM.

Technical Term	Value
Nameplate DC capacity	408.018 (kWdc)
Total AC capacity	500 (kWac)
Inverters—number and type	2 (SMA America: SC250U-480V)
Modules—number and type	1295 (SunPower SPR-315E-WHT-D)
Number of strings	185

The complete simulation file and related Excel files are available in [60]. SAM provided the PV system designed and several reports presenting hourly and monthly power productions. Figure 7 illustrates the differences between the energy estimated by SAM and the actual data especially for the months of February and July. The purpose of this work requires to focus on the cold months of the year to apply the snow-related rules. Therefore, we excluded the hot months of the year or months with no snow. As observed in Figure 7, the differences between the power estimations reported by SAM and collected onsite were significant for the three months of January, February, and December. We argue that SAM failed to contemplate the effect of snow. The application of the ontology model can provide more accurate results in power estimations for the three snowy months.

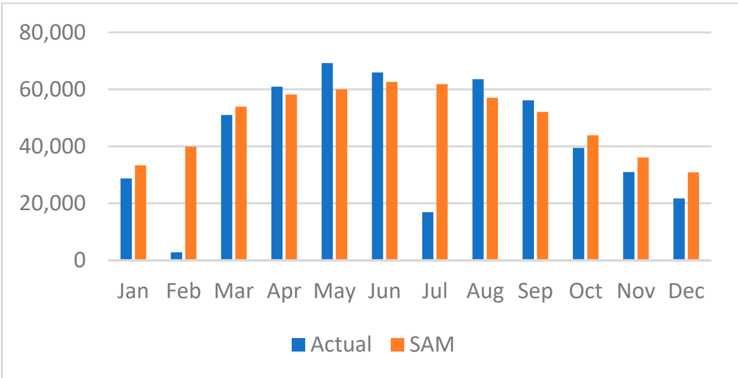

Figure 7. Power production (kW): actual measured onsite by NREL, and simulated by SAM.

5.1. Adjusting Hourly Power Estimations Using the SWRL Rules

The following steps present the processes of applying the rules for adjusting hourly power estimations reported by the SAM software for the case study.

5.1.1. Investigating Environmental Factors at the PV Site

In the first step, ambient conditions of the case study were investigated to determine the environmental factors that might affect snowfall. These factors can be detected as airborne particles due to pollution and air quality of the location. Therefore, the air quality of the site was inspected. There are six criteria pollutants for which the United States federal government has launched several standards in the Federal Clean Air Act and its amendments [92]. Among diverse elements, carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and lead (Pb) are concerned directly to protect sensitive members of the population. Two standard size fractions were considered for these measures: $PM_{2.5}$ and PM_{10}. These measures were set to protect such factors known as "visibility in scenic areas" [92]. They could affect the results of PV power productions due to the severity of shading that originally happened because of snowfall. The standard level of $PM_{2.5}$ was set at 15 μg/m^3 (averaged over 3 years) and 150 μg/m^3 for PM_{10} for the location of the PV system, Golden, CO. The NREL site experienced no exceedance of particulate matters of both $PM_{2.5}$ and PM_{10} for 2012, which are the most recent data available. The pollution data indicate that particles with the source of air pollution cannot affect the PV productions for the NREL site plant. Hence, none of the rules were applied for the adjustment of power outputs reported by SAM considering airborne particles.

5.1.2. Studying Climate Conditions of the Site Location

Comparable with the previous step, climate and weather terms of the PV plant were reviewed to define whether the snow rules are relevant or not. Cold months with a maximum possibility of precipitation were detected. This helped us to predict durations of shadings. Furthermore, weather related elements, including humidity, wind speed, and elevation of the environment can influence the impact of snow and consequently PV shadings. For instance, wind can blow away the PVs covered by snow or change the shading conditions and create partial shadings. In addition, humidity, especially at high temperature, makes the surface of a PV module suitable for airborne particles to remain on the surface, causing extended shadings.

5.1.3. Defining Shading Conditions due to Snowfall

By reviewing snow data, the exact days and hours of snow can be defined in addition to snow depths. In this way, durations of snow-covered modules were determined as well. The data about snow depths, durations, temperatures, and severity of precipitations aided us to detect the shading status of PV panels. It also identified whether full shadings occurred. In the case of full shading, there were no PV productions because no irradiance reached the surface of the PV modules. At the end of this phase, the affected hours of shadings and their snow depths were spotted. It is crucial to mention that there was no maintenance at the site for snow removal. Hence, snow shedding was considered as the only reason for clearing the surface from surfaces of the solar panels. Table 5 shows the information about shading conditions for the case study, including the date, depths of snowfall, and the detected full shadings.

5.1.4. Applying the Applicable Rules to the Hourly Productions

The rules had to be implemented to the hourly power estimations of SAM. These rules introduced correction factors needed for the affected hours of shadings. The exact dates and durations of shadings for our case study were already identified. Thus, the correction factors were applied to the affected hours in the SAM's Excel files for the related months. These files include the hourly power estimations for the three months of predicting shading conditions. Table 6 presents information about snowfall, including days and depths for the considered months.

Table 6. PV shadings information for the case study (RSF2).

Month	Snow Data
Jan	(7th–22nd) > 2.54 (cm), (17th–19th) < 2.54 (cm)
Feb	(3rd–22nd) and (23rd–25th) > 15 (cm) full shading
Dec	(19th–21st) > 15 (cm) full shading, (24th–29th) > 2.54 (cm)

Now, we needed to review the rules defined in the SQWRL plug-in to identify the applicable rules. The applicable rules can be found in the SQWRLTab environment as:

- Rule P28 (Shading Condition 26)—Snow Depth More Than 2.54 (cm)

The application of rule 28 recommends that snow depth of more than 2.54 (cm) causes 45% of daily loss for a 30° module angle and causes 26% of daily loss for 40°. Tilt angles were not considered as the main factor of changing parameters herein. The PV arrays were designed in a fixed angle (30°) in our SAM simulation for the case study.

- Rule P29 (Shading Condition 29)—Snow Depth Less Than 2.54 (cm)

Applying rule 29, which is about snow depths of less than one inch, cause a 11% daily loss for a 30° module angle and a 5% daily loss for 40°.

5.1.5. Implementing the Rules to the SAM Report

The applicable rules had to be implemented to the hourly power estimations for the days of shadings defined in Table 6. The power reductions were applied to the affected days in the Excel file of SAM created for the case study. As a result, the new Excel file represents the application of the ontology model, named as MPPT-On results hereafter. In the next section, these adjusted hourly power productions were compared with the actual power productions measured onsite.

6. Discussion and Analysis of the Results

Taking the previous step built the third set of data for the case study (RSF 2), the application of MPPT-On. The first set of data is the simulation results created by SAM. The second set of data is the hourly power production measured at the site (the data are available on the SAM website [90]). The complete output reports and the associated Excel files can be found in [60]. With regard to the zero productions, it is crucial to emphasis that we took into account every zero productions in our study regardless of their origins. The fact is that the purpose of the analysis indicates which output data should be weighted more.

To project a better understanding of the results, the t-test was implemented for the three sets of data. To perform the t-test, the hourly data with no power generations were removed from the datasets. The data for night-time hours, system shutdowns, and any type of system interruptions, causing zero PV productions, were eliminated. It is crucial to notify that when the full shading was happening, the hourly results related to the rules and onsite were arbitrarily defined as 0.1515 (hourly production of zero is stated as −0.1515 in the SAM files). The reason is that to separate hours with no production results caused by night times and system failures with the hours of full shadings. In this way, full shadings hourly data were included in the t-test. In the second phase, the ratios of SAM/onsite and MPPT-On/onsite were produced. Then, the three sets of data for shading hours of December, January, and February were gathered. In the final stage, the t-test was performed for each month representing samples of hourly results when shadings occurred. The one tail t-test formula in Excel was used for calculating the results of the table, considering $p = 0.05$. It is defined that if the null hypothesis was rejected, it was interpreted as significant differences between the forecast accuracy of SAM and the rules. Taking these steps, the monthly power productions for the case study (RSF 2 PV project) are presented in Table 7. As observed, the p-value results for every month with snowy days were significantly lower than $p = 0.05$. The p-value results for the months of February and December demonstrated that the application of the snow-related rules corrected the power estimations reported by SAM for the case study.

Table 7. T-test results for the application of rules (MPPT-On results), SAM estimations, and onsite measures of total hourly power productions for the case study.

Month	Onsite *	SAM *	Rules *	Shading Hours	SAM/Onsite *		Rules/Onsite *		p-Value
					Mean	ST. Dev.	Mean	ST. Dev.	
Jan	2346.99	5288.22	3240.35	47	389.811	563.468	102.209	203.819	0.0009
Feb	39.54	36731.67	39.54	261	928.94	617.641	1	0	4.4×10^{-69}
Dec	4054.73	11,572.01	853.34	105	504.572	530.747	1.501	7.242	1.5×10^{-16}

* Power production (kW).

Although the results of the three months indicate the significant effectiveness of snow-related rules, power adjustments for the other cold months of winter were noticeable as well. As observed in Figure 8, the overestimated powers reported by SAM were reduced perceptibly for the months of March, April, and October.

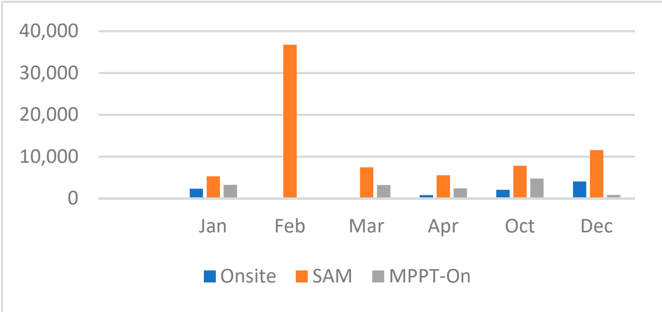

Figure 8. Power production (kW): measured onsite by NREL, simulated by SAM, and estimated based on the application of MPPT-On (rules applied to the SAM results) for snowy months.

The application of the proposed model and the rule-based system was independent from the technical characteristics of the PV system, ambient conditions, geographical parameters, and different formats of weather data (TMY or P50/P90) used by the simulation model. MPPT-On depended on the rules defined in the rule-based system. Thus, if the impact of a specific factor, for instance altitude, on PV shading was included in the model, it could be applied for manipulating the power estimations.

7. Conclusions

In this paper, we demonstrated the application of Semantic Web technologies in solar PV systems by proposing an ontology model. The model consists of essential parameters and factors which are required for designing MPPT controllers. These parameters were presented in the form of OWL class axioms. Characteristics of the classes were defined as objective properties and data properties. Furthermore, the developed knowledge-based model represented MPPT methods with a focus on an SWRL reasoning that provides information about power reductions caused by snowfall, clouds, and several airborne particles, including dust, sand, red soil, ash, calcium carbonate, and silica gel. The role of inclination was also defined in the rule-based system. The proposed model was validated using a real-world PV project as the case study. We showed that the application of the proposed model improved the power estimation reports of PV planning software failing to consider shading conditions. MPPT-On offered power corrections regardless of the technical characteristics of the project or the simulation used in the planning tool. The effectiveness of the model depended on the defined rules and correction factors outlined in the rule-based system. Furthermore, in addition to the rule-bases system, the proposed model offered valuable planning and designing recommendations in the form of queries. The SQWRL rules acted to evoke information out of the ontology model instead of manipulating data or changing values of a class assertion.

To extract information about MPPT methods and applying the rule-based system, the ontology model needed to be run in the Protégé environment. In future work, this setback can be eliminated by developing an application to automate the process of navigating the ontology. Furthermore, defining different rules addressing various ambient conditions and climate related factors, especially temperature, could help to improve the functionality of the proposed model.

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