An Ontology for Solar Irradiation Forecast Models

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Abstract: The growth of solar energy resources in recent years has led to increased calls for accurate forecasts of solar irradiance for the reliable and sustainable integration of solar into the national grid. A growing body of academic research has developed models for forecasting solar irradiance, identified metrics for comparing solar forecasts, and described applications and end users of solar forecasts. Ontologies are explicit and formal vocabulary of terms and their relationships that facilitate better communication, improve interoperability, and refine knowledge reuse by experts and users of the domain. This paper describes a step towards using ontologies to describe the knowledge, concepts, and relationships in the domain of solar irradiance forecasting to develop a shared understanding for diverse stakeholders that interact with the domain. A preliminary ontology on solar irradiance forecasting, SF-ONT, was created and validated on three use cases.

1 INTRODUCTION

Spurred by declining photovoltaic (PV) module prices, favorable government policies, and growing concerns about mitigating climate change, recent years have seen a rapid growth in the proliferation of solar electric systems. As PV markets continue to grow, the *variable*, *intermittent* and *non-dispatchable* nature of solar energy introduces additional uncertainty and variability in grid operations (Widiss and Porter, 2014). High-precision forecasts of solar energy output can prove crucial for the reliable, affordable and sustainable grid integration of solar electric systems (Diagne et al., 2013).

Solar irradiance forecasting (a proxy for solar energy forecasting) is an emerging knowledge domain that integrates expertise from diverse fields - researchers advancing forecast models, regulatory agencies developing performance characteristics, developers and practitioners integrating solar into the grid and so on. Due to differing technical backgrounds, expertise, knowledge hierarchies, terminologies, technical knowledge, and expectations, these diverse stakeholders may lack a shared understanding of the domain in which they interact.

Modern ontologies have emerged as a way to share common understanding of structure of information between communities of interest, either human or software agents. By separating domain knowledge from operational, ontologies promote interoperability, translating between different methods, models and paradigms (Noy et al., 2001).

A literature review reveals no comprehensive semantic ontology or application of semantic ontologies to represent information and knowledge about the domain of solar irradiance forecasting. In anticipation of a rapidly growing market in solar energy generation and integration in the electric grid, we present a solar forecasting ontology (SF-ONT) that covers solar forecasting models, their performance metrics, likely end-users, and grid applications. This ontology is then is validated on hypothetical use cases likely to be experienced by sample end-users.

2 RELATED WORK

To develop an ontology for solar forecasting it is necessary to understand about the forecasting problem itself, the many models that have been applied to this problem, the users and entities that may use the models, applications for which the models help answer questions, metrics to compare models, and what other ontologies exist for these topics. Each of these points will be briefly addressed in this section.

Solar energy output of a solar PV system is a function of physical characteristics of the solar PV system and the short-wave solar radiation flux incident on it's surface (McEvoy et al., 2011). This solar

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irradiance is a sum of many parts. At the top of the atmosphere, solar radiation is constant over time. Cloud cover, aerosol and dust particles absorb and scatter radiation as solar irradiance passes through the atmosphere. Consequentially, the solar irradiance that reaches any point on earth's surface is a function of atmospheric and weather conditions above the location of interest. All solar irradiance forecast models offer a means to capture this relationship.

We review widely used forecast models, with consideration given to their temporal and spatial forecast horizons (Figure 1). *Persistence Models* are naive models that assume solar irradiance at current timestep persists till the next; used for short term forecasts to benchmark other models. *Empirical Models* are based on empirical observations, not the physical relationships among inputs to the model; examples include sunshine based, temperature based, and ASHRAE models (Paulescu, 2008).*Radiative Models* employ remote sensing instruments on satellites or ground measuring stations that model irradiance as a function of altitude, location and atmospheric conditions on clear sunny days (Ruiz-Arias and Gueymard, 2018). *Time Series Models* forecast trends in solar irradiance based on statistical modeling of observed patterns in the past. Several categories of models include ARMA, ARIMA, ARIMAX, seasonal-ARIMA, etc. (Prema and Rao, 2015).

Artificial Neural Network (ANN) Models are general purpose computational intelligence machines that can be trained to learn and recognize patterns using atmospheric variables and time-series irradiance data as inputs (Voyant et al., 2017). *Cloud Imagery Models* use satellite derived models or ground-based sky imaging cameras to estimate cloud cover as an inverse proxy for solar irradiance (Barbieri et al., 2017). *Numerical Weather Prediction (NWP) Models* treat the atmosphere as a fluid, using thermodynamics to estimate the state of the fluid in the near future and producing forecasts of about 125 weather variables including solar irradiance (Reikard et al., 2017).

Accurate solar forecasting has applications offering value to multiple stakeholders in the electric grid. Long-term forecasts of utility-scale solar may be used for reliability planning and scheduling generation sources. Medium-term forecasts of roof-top solar at the distribution end may be employed in forecasting demand within a load-serving entity's service territory. Competitive electric markets may use short-term solar forecasts for bidding and trading energy services. Table 1 offers a summary of solar forecasting applications, end users and temporal domains in the context of the North American electric grid.

Questions stemming from a specific grid opera-

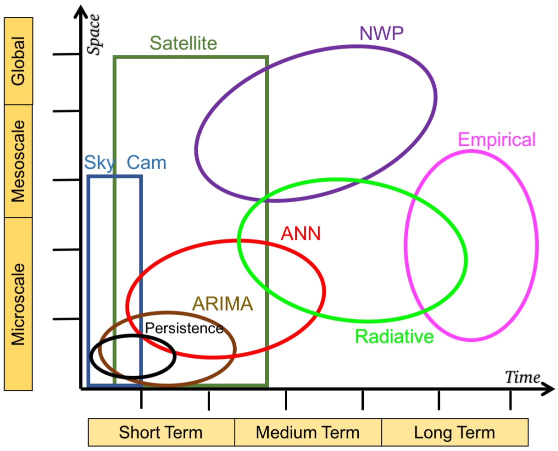

Figure 1: Spatial and temporal domains of solar irradiance models, adapted partly from (Pelland et al., 2013; Diagne et al., 2013).

tions application can be linked to a irradiance forecasting model type via the temporal domain. For example, a utility performing systems planning out for several years (long term horizon) would not want to consider a persistence irradiance forecast model (which is valid for short term time scales). Similar links via the spatial domain are also applicable.

Accurate solar forecasts facilitates more efficient integration of solar into utility resources. It is important to develop metrics to measure and assess the impact of forecasts have on integrating solar into the national grid (Zhang et al., 2015). The United States' Department of Energy Sunshot Initiative identifies criteria that makes a solar forecasting model useful - simple and easily understandable; provides actionable insights; input data is manageable and acquirable; and practical for operational and planning decisions.

The solar forecasting ontology presented here is novel to the literature, however, a few other related ontologies exist (note, ontologies which are incorporated into SF-ONT are discussed in detail in Sec. 4.1). Solar radiance is featured as one of many environmental or meteorological variables in ontologies like EEPSA (Esnaola-Gonzalez and Bermudez, 2015) and SREQP (Sánchez-Cervantes et al., 2016), without description of crucial attributes like forecast models, duration, resolution and so on. While SF-ONT describes models for solar energy generation, ontologies like Fiesta-Ont (FIESTA-IoT, 2017) and Poweront (Bonino et al., 2015) describe smart-home appliances and other demand side energy management services. As smart-grid research and development continues to drive support for unified semantic ontology for energy management (Cuenca et al., 2017), future updates to SF-ONT and related ontologies may im-

Table 1: Solar forecasting end-users, applications, and time-horizon; adapted from (Widiss and Porter, 2014; Zieher et al., 2015).

Users	Applications	Time-Horizon
ISO/RTO	Reliability planning	Long Term
	Congestion management	Medium Term
	Unit commitment & dispatch	Short & Medium Term
	Load-flow, ramps & curtailment	Short & Medium Term
	Security. maintenance & outage	Medium & Long Term
Distribution Utilities	System planning	Long Term
	Outage management	Medium Term
	Load forecasting	Medium Term
	Smart Grid management	Short & Medium Term
Load Serving Entity	Scheduling & balancing	Short & Medium Term
Energy Traders	Bidding strategies	Short & Medium Term
Research labs Project developers	Integration & simulation studies	All Terms

prove their interconnection and interoperability.

Some recent work describes the role of forecasts in managing power flow in smart grids. For instance, authors in (Maffei et al., 2018) describe an Artificial Neural Network (ANN) model that uses hourly energy and weather data to forecast solar irradiance. However, they do not offer a publicly available ontology, or provide insights into how this domain was mapped into the semantic vocabulary. Furthermore, the particular forecast model described in this paper with its specific inputs, outputs and other attributes can be easily modeled as an instance of the superclass *ANNmodels* in SF-ONT.

3 ONTOLOGIES

The domain of solar forecasting integrates knowledge from fields like cloud physics, statistical mechanics, artificial intelligence, grid-operations, and energy markets. Due to differing technical backgrounds, expertise, knowledge hierarchies, agents in the same environment may lack a shared understanding of the domain in which they interact. Natural differences in the definitions of concepts, structures, objects and relationships may lead to poor communication, reduced interoperability, and system integration challenges (Uschold and Gruninger, 1996). Ontologies have emerged as means to preserve interoperability, formally modeling domain knowledge using instances, sets of concepts, and relationships between sets of concepts (Guarino et al., 2009). While the features of an ontology can also vary by the language used to describe the ontology, this paper uses Web Ontology Language (OWL) to represent domain knowledge of solar forecasting models.

Web Ontology Language (OWL) (McGuinness et al., 2004) is a formal semantic language from the World Wide Web Consortium (W3C) that offers a rich set of differential logic operators (e.g., intersection, union), allowing for complex concepts and relationships to be built from simpler concepts. Any domain can be modeled through a shared vocabulary of individuals, properties and classes. *Individuals* represent objects in the domain of interest, explicitly defined as same or different to each other. Properties are the features and attributes of *Individuals*. *Classes* defined by the relationships between *Individuals*, or through a restriction on *Properties*.

3.1 Ontological Development Methods

Many approaches have been proposed for formally developing ontologies. Uschold and King is among the first ontology development methods published (Uschold et al., 1998). The approach uses an iteration through the following stages - identify domain vocabulary, purpose, intended use, end-users, scope, terms; capture and code textual concepts and relationships into formal ontological language; evaluate requirements; and document results from each stage to aid the next iteration of ontology development.

SENSUS is a natural language based ontology developed to provide a broad conceptual structure for work in machine translation. Rather than develop a step by step or iterative process, SENSUS outlines general principles for designing an ontology - Do not over-commit on representational choices; extend based on actual use conditions; integrate horizontally with other ontologies; and cluster concepts to structure ontologies (Swartout et al., 1996).

METHODONTOLOGY acquires, evaluates and documents domain knowledge through an iterative process of ontology *specification* (vocabulary, purpose, scope, term, and other factors); *conceptualization* (concepts, verbs, class attributes and instances of classes); *integration* (reusing existing ontologies); and *implementation* (check for incomplete, inconsistent and redundant knowledge) (Gruber, 1993)

This paper uses Ontology 101 (Noy et al., 2001) and the Prot*égé* software tool (Musen, 2015) to develop an ontology for solar forecasting. This method was chosen for its accessibility to modelers with limited prior experience and its flexibility of informal guidelines, providing multiple entry points into the process of domain knowledge translation.

4 SOLAR FORECASTING ONTOLOGY

The solar forecasting ontology (SF-ONT) developed in this paper integrates knowledge from academic papers, grey literature, as well as industry, government, and expert papers. This ontology is intended to be used by project developers to compare solar forecasting models, and choose an appropriate model for their use-case scenario, while working within the limitations of data and instrumentation availability.

4.1 Domain Knowledge Description

We will walk through a brief overview of the creation of the SF-ONT.

Competency Questions: Table 2 enumerates a sample of competency questions for illustrative purposes and identifies the important terms that need to be explained to the user. Our ontology will make 'statements' about these terms through relationships between them. At this stage, terms and relationships are expressed in the natural language without worrying about overlap of concepts. Competency questions were developed with collaborators for a research project on microgrids.

Related Ontologies: Reusing existing and validated ontology saves time and effort. Many concepts defined in an different ontology can be directly imported, with little modification, and applied to the domain of interest. The following formal ontologies were considered for reuse in SF-ONT.

- **OWL-Time** (W3, 2017) is a list of temporal concepts built for describing time related content of Web pages like *Intervals* - spans of time that have an beginning and an end, and *Instants* - intervals with zero length that are used to express notions of time time like duration, begins, ends, etc.
- **OWL-Basic-GEO** (W3, 2003) is a Resource Description Foundation (RDF) vocabulary that provides semantic definitions for basic geographic concepts like latitude, longitude and other spatial concepts.
- **Units of Measurement** (Rijgersberg et al., 2013) is an OWL ontology of the domain of measures expressed in terms of a base set of SI system of units. For example, electromagnetic irradiance is $W\ M^{-2}$.
- **Weather** ontologies that describe concepts from the domains of weather and weather forecasting were considered (W3, 2005; Gajderowicz, 2008; Staroch, 2013). However, these ontologies describe weather variables like sunrise time and windspeeds that are not relevant for SF-ONT's purposes. Since these ontologies reused modified concepts of OWL-Time and Units, we sought to avoid the risk of obfuscating domain knowledge due to overlapping classes, predicates and concepts.
- **Concentrated Solar Power** ontology, first developed by (Piazza and Faso, 2014), largely serves as a proof of concept for formally representing knowledge of solar radiation modeling and forecasting by the means of ontologies. However, the domain of this ontology is limited to just one type of solar energy systems - concentrated solar power systems, and does not include expertise on end-users and grid applications. Nevertheless, concepts like temporal and spatial domain of forecast models were reused for SF-ONT.

Defining Classes and Hierarchy: Using competency questions motivated above (examples in Table 2), we enumerated a list of concepts (terms and their properties), described either in terms of classes or individual instances. Classes are organized into a hierarchical taxonomy, where subclasses inherit the properties of their superclass and instance of a subclass by definition will be an instance of the superclass; see example in Figure 2. ANN is a subclass that inherits the properties and relationships of the class ForecastModels - *hasInputs* & *hasOutputs*. ANN_1 represents an individual instance of a class of ANN models such as one implemented in (Cuenca et al., 2017).

Defining Properties and Relationships: Classes can also be defined by the relationships between concepts. In Figure 1, short, medium and long terms are the temporal domains of forecast models can represented by classes and relations as shown in Figure 3. Relationships are explicitly encoded in the development process of the ontology where models like NWP are subclasses of the class ForecastModels, but are connected to the class MediumTerm through the relation *hasTemporalDomain*. Overall, the summary statistics and top-level classes of SF-ONT are presented in Figure 4. Full details of SF-ONT are available at http://pages.mtu.edu/ lebrown/research/sf-ont/.

Table 2: A sample of competency questions.

Competency questions	Class	Property	Class
What data do I need for my model to work?	ForecastModels	*hasInputs*	ForecastInputs
What models can I use with these weather variables?	ForecastModels	*hasOutputs*	ForecastOutputs
Can I use this model at this location?	ForecastModels	*hasGeographicAttr*	Lat & Long.
Who will use my forecast model and for what?	EndUsers	*isResponsibleFor*	Applications

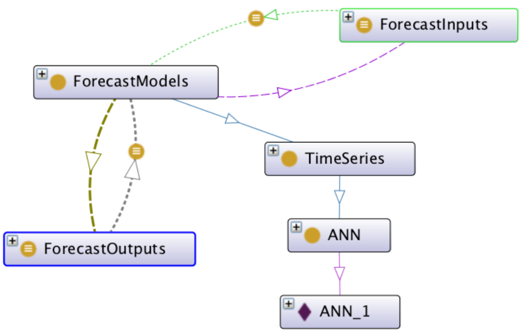

Figure 2: Example of hierarchy of classes in the ontology.

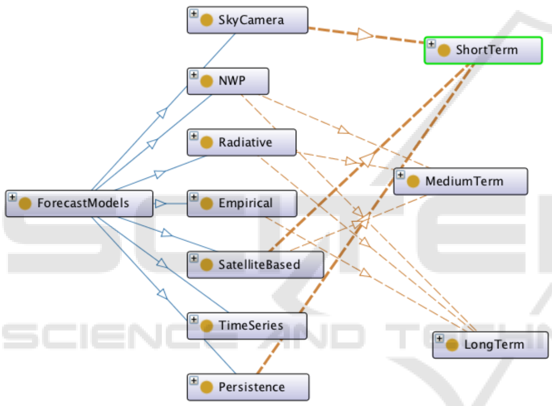

Figure 3: Example of relation between classes.

4.2 Testing and Validation of SF-ONT

Once domain knowledge has been explicitly specified, the semantics of an ontology are verified to avoid overlap of concepts and relationships. Simple reasoners check for logical consistency by testing if objects and properties are linked correctly based on defined rules and axioms. In the hierarchical model of classification, the Prot*égé* software environment that supports asserted hierarchies that are manually named and explicitly constructed; or inferred hierarchies that are that are not explicitly stated in the data model but instead are inferred using advanced reasoners. Such advanced reasoners help populate relationships between individuals in a domain without explicitly encoding every single relationship from the domain.

Beyond such logical checks, a systematic evaluation can help users make informed decisions about choosing an ontology that best fits their needs. Ontologies should be understandable, and offer a conceptual foundation for a range of anticipated uses. Ontologies have to be further validated to test that they address the requirements that motivated their creation. Validation of ontologies through illustrating use-cases is a common practice to determine if an ontology is accurate, adaptable and clear (Staab and Studer, 2013). Accurate ontologies comply to the knowledge experts of the domain, and correctly represent the concepts of the world. The use-cases that follow were developed in consultation with collaborative research projects on microgrids and by no means exhaustive, but serve as a means to illustrate the quality of the ontology.

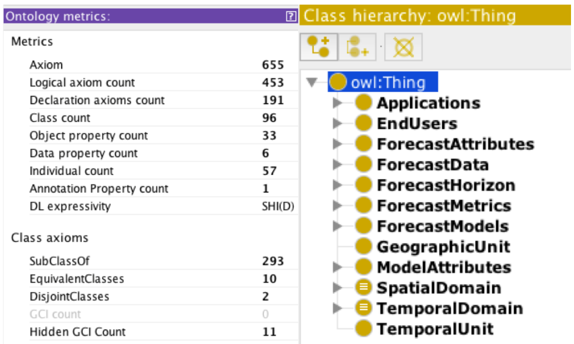

Figure 4: SF-ONT summary statistics and classes expressing top-level concepts in solar irradiance forecasting.

4.2.1 Identifying Appropriate End-users based on Constraint on Forecast Models

Consider a real world scenario where a research lab develops an ANN based solar forecasting model, and is interested in identifying the end-users that would benefit from such a model. In our domain knowledge of solar forecasting, end-users are not explicitly related to forecast models. However, in the Prot*égé* software environment, expert reasoners like FACT++ can be used to infer a relationship. For this use case, a new subclass ANNEndUsers, a subclass of EndUsers is specified using the class hierarchy relationships show in Figure 5. Figure 6 illustrates the populated *inferred* dummy class.

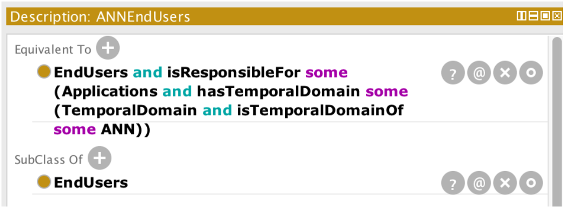

Figure 5: The asserted class relationships of a dummy class called ANNEndUsers.

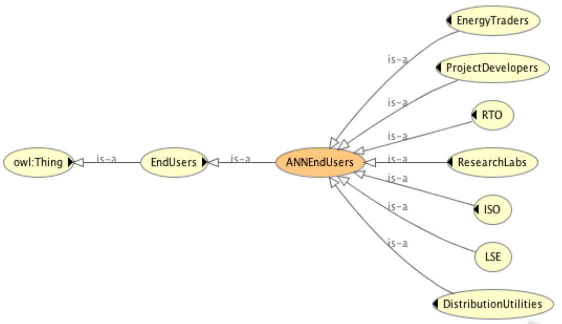

Figure 6: The inferred hierarchy of the ANNEndUsers class.

4.2.2 Identifying Appropriate Grid Applications based on Data Constraints

Consider a scenario where a solar developer wants to develop a forecast model to inform specific grid application, but is constrained by the kind of data variables available as forecast model inputs. In our domain knowledge of solar forecasting, grid applications are not explicitly related to input variables of forecast models. However, expert reasoners can be used to infer a relationship. For this case, a dummy class of applications that may use solar irradiance forecasts when only parametric constants are available is created (Figure 7) with the inferred hierarchy shown in Figure 8.

4.2.3 Selecting Appropriate Models based on Constraints on End-users

Consider a real world scenario where a programmer wants to develop solar forecasting tools for a specific end user, a Load Serving Entity (LSE) for instance. In this use case scenario, the developer is interested in identifying all solar forecasting models that could be used to forecast solar irradiance according to parameters that could most benefit their client. At this stage of the development process, the developer does not have the domain expertise to identify appropriate grid applications for their forecast model. A new subclass ModelsForLSE is created under ForecastModels to represent the desired class (see Figure 9). The inferred hierarchy of ModelsForLSE is shown in Figure 10.

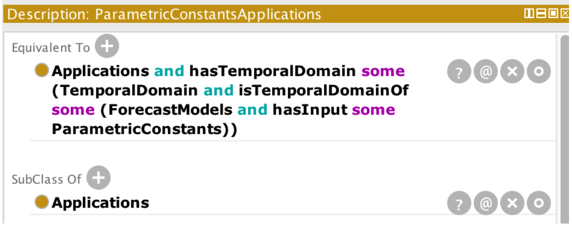

Figure 7: Example of identifying grid application based on data constraints - ParametricConstraintsApplications.

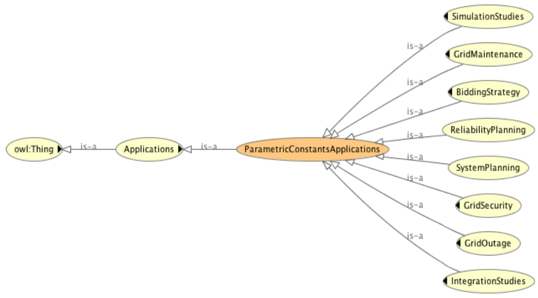

Figure 8: The inferred hierarchy of the ParametricConstraintsApplications class.

5 CONCLUSION AND FUTURE WORK

This paper describes the basics of solar irradiance and forecasting, reviews academic literature on recent advancements in improved solar forecasting models, and identifies grid applications and end-users that will benefit from accurate solar forecasts. In doing so, the paper integrates knowledge from a growing body of academic research advancing models for forecasting solar irradiance, with expertise from practitioners developing applications for integrating solar into the grid.

Due to differing technical backgrounds, expertise, knowledge hierarchies, terminologies, technical knowledge, and expectations, the diverse stakeholders in the world of solar forecasting may lack a shared understanding of the domain in which they interact. In anticipation of a rapidly growing market in solar energy generation and integration, this paper describes a step towards improving communication, interoperability and knowledge-sharing about solar forecasting, using ontologies.

Subsequently, the paper describes ontologies and briefly reviews methodologies for developing ontologies. Using Ontology 101, an ontology development methodology, the paper then describes SF-ONT - a formal ontology that maps the knowledge domain of solar irradiance forecasting. Finally, the paper des-

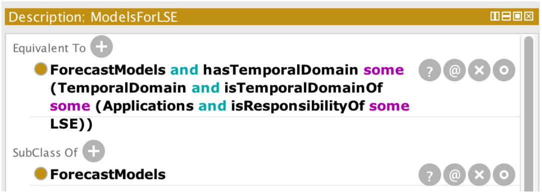

Figure 9: Class hierarchy relationship to identify class ModelsForLSE.

Figure 10: The inferred class hierarchy of ModelsForLSE.

cribes the testing and validating of solar forecasting ontology for accuracy and completeness using built-in Protégé software reasoners.

SF-ONT is presented as a starting point and a first step for co-creating a shared ontological mapping of the of the solar forecasting domain. Currently, SF-ONT identifies all the top level concepts in the domain of solar irradiance forecasting, and models their relationships within the context of the current knowledge in the domain.

As research advances forecast models with better spatial and temporal resolution, and as regulatory agencies continue to refine metrics for comparing forecast qualities, and as energy markets continue to evolve, SF-ONT will need to be updated to reflect the most current state of domain knowledge. New instances will have to be populated and existing relationships, properties and classes may have to be (re)defined. To facilitate reuse, duplication and updates, SF-ONT is made available at http://pages.mtu.edu/ lebrown/research/sf-ont/.

As knowledge in the domain expands, this ontology can be extended from the basic building box, modified and maintained to suit the evolving needs of the users. One priority area for SF-ONT extension is to capture domain knowledge of PV systems planning and design. For instance, concentrated solar plants (CSP) and utility-scale solar farms (USF) are high intensity generators directly connected to the transmission infrastructure and dispatched through energy markets, which calls for location specific forecasts at a high temporal resolution. By contrast, rooftop solar is connected to the distribution grid, often times 'behind the meter' with lower expectations for forecast resolutions.

Another priority area for extension is PV system security and cyber-security, with a particular emphasis on grid resiliency. The key challenge in this context will be preserving interoperability between different domains of knowledge as their formal ontologies are developed and mapped independently. In this context, future updates to SF-ONT may need to actively involve domain experts and end-users in the ontology development process. Ontology engineering methodologies like HCOME (Kotis and Vouros, 2006) empower domain experts and end users to "manage ontologies shaping their common information space", which can lead to richer, more relevant, and regularly updated "living" ontologies.

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