Interpretable data-driven solar power plant trading strategies

Konstantinos Parginos, Ricardo J. Bessa, Simon Camal, Georges Kariniotakis

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Konstantinos Parginos
MINES Paris, PSL University, Center PERSEE
Sophia Antipolis, France
konstantinos.parginos@minesparis.psl.eu

Ricardo Bessa
INESC TEC, Center of Power & Energy Systems
Porto, Portugal
ricardo.j.bessa@inesctec.pt

Simon Camal
MINES Paris, PSL University, Center PERSEE
Sophia Antipolis, France
simon.camal@minesparis.psl.eu

Georges Kariniotakis
MINES Paris, PSL University, Center PERSEE
Sophia Antipolis, France
georges.kariniotakis@minesparis.psl.eu

***Abstract*—Standard practices of decision-making in energy systems are dynamic, non-linear, complex, and chaotic processes in nature. Trading the power produced by solar photovoltaic (PV) plants in electricity markets is an important decision-making problem which receives increasing attention in the past few decades. The main objective of this paper is to build an interpretable data-driven decision aid model for the case study of a solar power plant with the objective to minimize imbalance costs and thus maximise the revenue, using Symbolic Regression (SR) through Genetic Programming. The use of SR in the experiments and analysis developed in this paper show numerous advantages. SR evolves linear combinations of non-linear functions of the input variables. Three penalty metrics are introduced to enhance the interpretability of the final solutions. SR shows robust results, especially in the case study.**

***Index Terms*—Artificial Intelligence, Renewables, Interpretability, Trading, Solar, Symbolic Regression, Genetic Programming**

I. Introduction

A. AI Applications in the Energy Sector

The Energy System in Europe is on a path of transformation that should allow it to achieve a net-zero emissions target by 2050. To achieve this target an increased penetration of Renewable Energy Sources (RES) is needed. The European Commission anticipates in its impact assessment a 40% renewables share, with 479 GW of solar by 2030 [1]. The increased capacity of solar production will correspond to increased importance of the decision making for trading the energy produced by PVs. Most solar plant trading strategies rely largely on complex modelling chains to address technical constraints and integrate numerous sources of uncertainty.

In this context, artificial intelligence (AI) based solutions are increasingly developed to simplify modelling chains, and to improve performances due to higher learning capabilities compared to state-of-the-art methods. The most important variable in decision making for trading strategies is the photovoltaic power forecast. Reviews of photovoltaic power forecasting methods in [2], [3] conclude that Artificial Neural Networks (ANNs) are the most used artificial intelligence technique in solar power forecasting, as they have a proven track record in terms of accuracy for a variety of situations and with numerous input variables. Decision-makers of the energy sector need to understand how decision-aid tools construct their outputs from the data representing such dynamic multi-scale systems. ANNs for different management functions of the energy system are often seen as black-box models and this penalizes their acceptability by the end-users (traders, power system operators a.o.). The lack of interpretability of AI tools is a major challenge for the wider adoption of AI in the energy sector and a fundamental requirement to better support humans in the decision-aid process. Agents of energy systems expect high levels of reliability for the various services provided by these systems [4] (energy, ancillary services, flexibility, etc.): this ensures proper sizing of security measures and quality of service for end-users. Several papers propose AI-based solutions for trading renewables in a market structure similar to the one used in our case study [5] [6].

B. Interpretability

The terms interpretability and explainability are sometimes used interchangably [7]. Most of the time both Interpretable AI and Explainable AI refer to Artificial Intelligence tools, in which the process of calculating the output can be understood by humans. It contrasts with the concept of the black box in machine learning where there is no explanation of why an AI arrived at a specific decision. An interpretable model should consistently estimate what the AI tool will predict given a specific input, understand how the model came up with the prediction and how the prediction changes if a change in the input or algorithmic parameters is made. Interpretability is mostly needed by experts who are either building, deploying or

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using the AI system. In this paper, we focus on an interpretabe decision-aid tool that uses symbolic expressions. To conclude we can define interpretability as a description of the model, which enables us to control the outputs according to the inputs.

C. Symbolic Regression as a Way to Enhance Interpretability

Symbolic Regression (SR) is a form of an evolutionary algorithm which is inspired by the principles of Darwinian evolution theory and natural selection [8]. The broader domain where SR belongs is called Genetic Programming (GP) and is a domain-independent modelling technique that creates mathematical models based on data sets that describe complex problems or processes. The biggest advantage of SR is the ability to automatically evolve both the structure and the parameters of the mathematical model. This attribute provides the flexibility for a data-driven, non-linear model output that represents an interpretable relation of the input features.

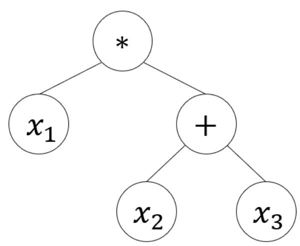

Fig. 1. Example of a tree representation of a Symbolic Equation.

As is illustrated in Fig. 1 the SR models are represented in a tree-like structure, where nodes represent the functions and leafs represent the variables which construct the end solution. In the specific paradigm of Fig.1 the tree represents the equation:

$$y = x_1 * (x_2 + x_3) \tag{1}$$

where x_1, x_2, x_3, are the feature variables and y is the target variable.

D. Objectives & Contribution

Combining the predictive power of Artificial Intelligence models with interpretable features has attracted a high interest within the fields of computer vision and natural language processing as the most common areas of interpretable algorithm applications [9], [10]. The research dedicated to the interpretability of time series is still understudied [11]. To the best of our knowledge, SR has not been applied to decision-making tools for trading strategies for Solar PV power plants. Our key contributions are summarized as follows:

1) We propose and validate the use of an alternative data-driven modeling approach that leverages GP to obtain interpretable trading strategies.
2) We introduce a penalty metric that reduces symbolic expression complexity by penalizing each expression with the number of operations occured.
3) We illustrate the applicability of SR in the energy sector and more precisely to a renewable trading case study of minimizing imbalance costs.

We believe that the use of this penalty could enhance interpretability in various sections and applications of SR.

Our methodology performs three different classifications of the data before applying SR to achieve human-friendly set of rules according to metrics that are already used by expert traders to classify the situation of the market. The classifications are based on the hour of the day, the imbalance of forecasted prices and the critical quantile.

The rest of the paper is organized as follows. Section II presents the mathematical background and the proposed methodology. Section III formulates the trading problem and the fitness function of our case study. Results are presented in Section IV. Finally, we draw conclusions and provide directions for future research in Section V.

II. Methodology

A. Formulation of Symbolic Regression

Following the formulation proposed by [12] we could define Symbolic Regression, as the process of learning a mapping $\hat{y}(x) = \hat{\Phi}(X, \hat{\theta}) : \mathbb{R}^{n \times m} \to \mathbb{R}^n$, using a dataset of paired examples $\mathcal{D} = (x_i, y_i)_{i=1}^m$, with features $X \in \mathbb{R}^{n \times m}$ be an $n \times m$ matrix where each column $x_i \in \mathbb{R}^n, i = 1, \ldots, m$ is an n-dimensional input variable and each row $s_j \in \mathbb{R}^m, j = 1, \ldots, n$ is an m-dimensional training sample. For this paper we define X as the training data for the algorithm and as $y \in \mathbb{R}^n$ the target vector for the regression problem.

The GP primitive set is defined as $\mathcal{P}$ and as $\mathcal{S}$ the syntactic search space defined by it. We further define Φ as the space of possible expressions and their parameters. That is, the set of all tuples (E, θ), where $E \in \mathcal{S}$ is a symbolic expression and $\theta \in \mathbb{R}^p$ a parameter vector of length p corresponding to the hyperparameters of E. Let us call a tuple (E, θ) a symbolic expression model $\mathrm{M}_{E,\theta} \in \Phi$.

For SR to conclude to an analytical model, we claim that $G : \Phi \times \mathbb{R}^{n \times m} \to \mathbb{R}^n$ is a function that evaluates a model $\mathrm{Z}_{E,\theta} \in \Phi$ on training data X and returns an n-dimensional output vector $y \in \mathbb{R}^n$:

$$\hat{y} = G(\mathrm{Z}_{E,\theta}, X) \tag{2}$$

The goal of the evaluation is to estimate the optimal model by searching the space of expressions Φ and parameters θ.

$$\mathrm{Z}_{opt} = (E_{opt}, \theta_{opt}) \tag{3}$$

To achieve this goal we need to minimize a predefined fitness function $\mathcal{L}$:

$$\mathrm{Z}_{opt} = \arg \min_{\mathrm{Z}_{E,\theta} \in \Phi} \mathcal{L}(G(\mathrm{Z}_{E,\theta}, X), y) \tag{4}$$

B. Genetic Programming

To achieve the optimal model Z_{opt}, SR should iterate through the GP algorithm. As illustrated in Fig.2, there are five steps that construct the algorithm.

A predefined function set and a set of features is been randomly combined and form an initial population of random symbolic programs, called individuals. Each individual is characterized by a fitness value, according to it, part of the

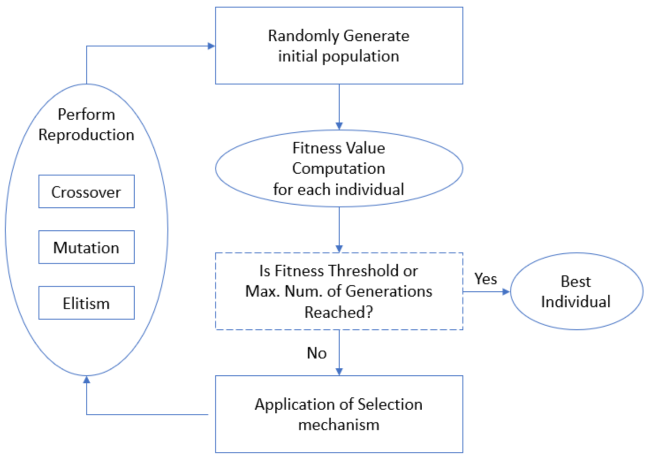

Fig. 2. Genetic Programming algorithm.

population is chosen for reproduction in the so called survival of the fittest mechanism. Reproduction is the core of genetic programming. Each generation is formulated according to the results of different genetic operators, including crossover, mutation and elitism. More details on how those operators form the next generation can be found in [8]. Finally the GP algorithm terminates when a defined number of generations or when a threshold to the fitness value has been reached.

C. Fitness & Penalty Metrics

To perform the second step of the GP algorithm, different fitness metrics can be used. In this paper we are focusing on the interpretability of SR outputs, thus we want to heavily penalise solutions with high complexity (multiple nodes and leafs of the tree structure).

The fitness function $\mathcal{L}$ can be split into two parts, the raw fitness $\mathcal{L}_{raw}$ of a specific case study and a penalty metric $w_{interpret}$.

The penalty metric introduced in this paper is in line with the main focus of this paper, with a goal to enhance the interpretability of trading decision aid tools.

$$\mathcal{L} = \mathcal{L}_{raw} + w_{interpret} \tag{5}$$

The raw fitness $\mathcal{L}_{raw}$ could be a widely used statistical metric as square mean error when we want to approximate a specific y target. We could also define a model specific raw fitness metric, as performed in the case study analyzed in this paper with the introduction of Imbalance Penalties as $\mathcal{L}_{raw}$.

As illustrated from the example in "Fig. 1", we can calculate the length of the mathematical model Z as the total number of nodes and leafs. In the example of (1) we observe a $len(Z) = 5$. By having a metric of the expression length we can control the complexity of the SR outcome.

Assuming that each node (function) requires two leafs (variables), calculating the number of operations used in each individual symbolic equation of the same population is performed by the following equation:

$$op(Z) = \frac{len(Z) - 1}{2} \tag{6}$$

In "Fig. 1" we observe a total $len(Z) = 5$ and as expected, in (1) we observe a total of $op(Z) = \frac{5-1}{2} = 2$ operations.

This paper introduces the number of operations occurred in a symbolic expression as a penalty metric that enhance model interpretation. Let's define k as the index of each individual model Z_k, then each model is penalized with the number of operations occurred at Z_k.

$$w_{interpret,k} = op(Z_k) = \frac{len(Z_k) - 1}{2} \tag{7}$$

III. Case Study

In this paper, we do not aim to further improve the revenue generated from state of the art methods, but rather to improve the transparency of our models by creating data-driven ad-hoc interpretable strategies that perform equally well. We derive to the ad-hoc interpretable strategies by the use of SR with a custom fitness and a penalty metric introduced in Section II.

We compare the revenues observed during a period of 11 months, which we split in training, 1st of May 2016 - 30th November 2016, and testing, 1st of December 2016 - 31st of March 2017, subsets accordingly. The PV plant is located in France, with a total capacity of 2.7 MW. NWPs are obtained from the European Center for Mediumrange Weather Forecasts (ECMWF). We use prices of France from EPEX SPOT.

A. Trading in Day-Ahead Market

We consider trading in a Day-Ahead (DA) market as a price-taker according to formulations of [13]. The decision maker submits an energy offer p^{offer} before the closure of the market. In order to maintain the demand-supply adequacy and stabilize the system frequency, the system operator activates balancing reserves during real-time (RT) operation. The system could be found in two states, either short, i.e., demand exceeds supply while upward regulation is required, or long, i.e., supply exceeds demand while downward regulation is required. According to RT stochastic renewable production pE, the producer buys back or sells the amount of energy shortage or surplus in order to balance its trading position. We define π^{da} as the clearing price of the DA market and $\pi^{\uparrow/\downarrow}$ the marginal cost of activating upward/downward regulation services. We assume that if the system is short, then $\pi^{\uparrow} \geq \pi^{da}$ and $\pi^{\downarrow} = \pi^{da}$; while if the system is long, then $\pi^{\downarrow} \leq \pi^{da}$ and $\pi^{\uparrow} = \pi^{da}$. Let us further define $\lambda^{\uparrow} = \max\{0, \pi^{\uparrow} - \pi^{da}\}$ and $\lambda^{\downarrow} = \max\{0, \pi^{da} - \pi^{\downarrow}\}$ as the upward and downward unit regulation costs accordingly. With that being defined, we conclude that $\lambda^{\uparrow} \cdot \lambda^{\downarrow} = 0$, i.e., only one of them assumes a value greater than zero for a given settlement period t. For a single period t, the profit is defined as:

$$\rho^{\text{dual}} = \pi^{da} p^E - \underbrace{\left[-\lambda^{\uparrow}(p^E - p^{offer})^{-} + \lambda^{\downarrow}(p^E - p^{offer})^{+}\right]}_{\text{imbalance cost}} \tag{8}$$

where $(\cdot)^- = \min\{\cdot, 0\}$ and $(\cdot)^+ = \max\{\cdot, 0\}$.

The imbalance cost term is always $non-negative$, which means that no additional profit can be attained in the balancing market. Here, $\{p^E, \lambda^{\uparrow}, \lambda^{\downarrow}\}$ defines the uncertain problem parameters. Since profit is affine with respect to the contracted energy, following [13] we derive energy offer analytically as:

$$p^{offer*} = \hat{F}^{-1}(\tau) \tag{9}$$

with τ being:

$$\tau = \frac{\hat{\lambda^{\downarrow}}}{\hat{\lambda^{\downarrow}} + \hat{\lambda^{\uparrow}}} \tag{10}$$

and $\hat{F}^{-1}$ being the predicted inverse cumulative distribution function (c.d.f.) of pE. This analytical expression of p^{offer} will be used as the reference for our case study.

B. Fitting the SR for Trading

The goal of the SR fitness function of this case study is to minimize the imbalance cost term of (8) and can be defined as:

$$G_k = -\lambda^{\uparrow}(p^E - p^{offer})^- + \lambda^{\downarrow}(p^E - p^{offer})^+ \tag{11}$$

where k is the index of the SR model Z_k and p^E is the target vector y. We can now define the set of L_{raw} fitness metric as:

$$\mathcal{L}_{raw} = \arg\min\{G_0, G_1, ..., G_n\} \tag{12}$$

Now that the functions $\mathcal{L}$ have been defined we could run the SR to derive to the optimal model $Z_{opt} = (E_{opt}, \theta_{opt})$, that produces the trading decision $y_{opt} = p^{offer}$.

C. Trading Strategies Classification

We propose three different classifications of the data before applying SR in order to achieve human-friendly set of rules according to metrics that are already used by expert traders to classify the situation of the market and proceed with the use of an interpretable model for their decision accordingly. As illustrated in "Fig.4", the classification is based on:

1) h: the hour of the day
2) τ: the critical ratio or quantile
3) $\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}$: delta of Up/Down regulation forecasted prices

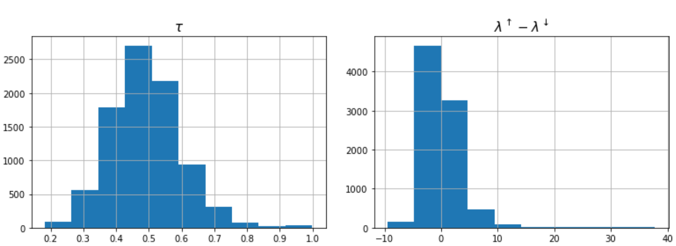

Fig. 3. τ and $\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}$ distribution

Hourly data are equally distributed in our dataset and thus we cluster our data by 14 sub-samples from 06.00 till 19.00. The subsets for the τ and $\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}$ were created according to their distribution as illustrated in "Fig. 3".

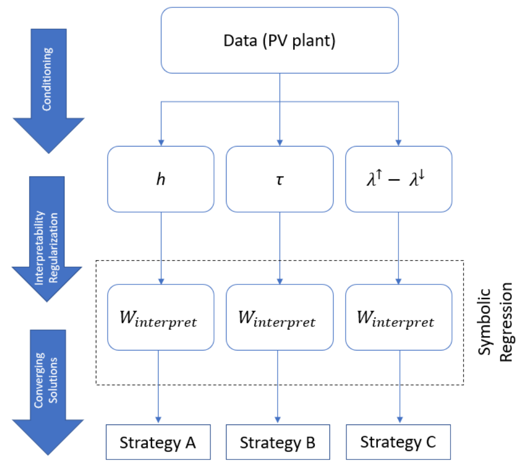

Fig. 4. Flow Chart

IV. Results

Table I, illustrates the trading strategy A, derived by a SR for each hour of the day between 06.00 and 19.00. Between 08.00 and 16.00, that solar production peaks, we observe a simple trading decision of bidding the forecasted power production $p\hat{E}$ with some fine tuning according to the imbalance prices ($\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}$) and the temperature ($NWP_{temp}$) observed. SR introduced $Load$ as a variable to be considered during the early morning and late afternoon ramp up hours. More precisely for 06.00, 07.00 and 17.00, 18.00 o'clock we can observe the inverse correlation with the $Load$ as well as the introduction of the W_{CLS} in the symbolic expression, which corresponds to clear sky metric.

TABLE I
Trading Strategy A

Time	Strategy	Time	Strategy
06.00	$p\hat{E} + \frac{0.08}{Load^2}$	13.00	$p\hat{E}$
07.00	$\frac{3W_{CLS}\hat{\lambda^{\downarrow}}}{Load}$	14.00	$p\hat{E}$
08.00	$p\hat{E}$	15.00	$p\hat{E}$
09.00	$p\hat{E} - \frac{2\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}}{NWP_{temp}}$	16.00	$0.98p\hat{E}$
10.00	$p\hat{E}$	17.00	$\frac{\hat{\lambda^{\downarrow}} 2W_{CLS}Load(\hat{\lambda^{\downarrow}}+1)+0.38\hat{\lambda^{\downarrow}}}{Load^2}$
11.00	$p\hat{E}$	18.00	$p\hat{E} + \frac{0.07}{Load^2}$
12.00	$p\hat{E} - \frac{2\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}}{NWP_{temp}}$	19.00	0.00

Tables II present in detail the resulted interpretable strategy for Strategy B. For the Trading Strategy B, SR is applied according to the value of τ metric. For the majority of the data-points, $\tau \in [0.4-0.7]$, we observe an analytical expression that includes the forecasted power $p\hat{E}$ and $Load$. SR also introduce the prediction interval $Q90$ that corresponds to the difference between 95th-5th quantile of the forecasted power $p\hat{E}$. $Q90$ is introduced for the market conditions that τ metric is equal to 0.5, in which $\hat{\lambda^{\downarrow}} \simeq \hat{\lambda^{\uparrow}}$. For extreme values of τ SR concludes to bid almost 0 MW to avoid any imbalance costs.

TABLE II
TRADING STRATEGY B

τ	Strategy
<=0.2	NWP_{tcc}
[0.2 - 0.3]	$p\hat{E} + 0.017 + \frac{\hat{\lambda^{\downarrow}}}{NWP_{temp}}$
[0.3 - 0.4]	$p\hat{E} + 0.017$
[0.4 - 0.5]	$p\hat{E} + \frac{Load(p\hat{E}+Q_{90})+Q_{90}+0.022}{Load^2}$
[0.5 - 0.6]	$p\hat{E} + \frac{0.08}{Load^2}$
[0.6 - 0.7]	$p\hat{E} + \frac{0.08}{Load^2}$
[0.7 - 0.8]	$\frac{p\hat{E}\hat{\lambda^{\downarrow}}\hat{\lambda^{\uparrow}}+p\hat{E}\hat{\lambda^{\downarrow}}+0.02\hat{\lambda^{\uparrow}}}{\hat{\lambda^{\uparrow}}^2}$
0.8=<	0.00

Table III illustrates the results of SR trained on different clusters according to the $\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}$ difference. Despite the small increase in complexity of those expressions, they follow the same principles, of bidding a combination of $p\hat{E}$ and $Load$ with several variations according to the difference of imbalance prices.

TABLE III
TRADING STRATEGY C

$\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}$	Strategy
<-5	$p\hat{E} + \frac{NWP_{temp}}{Load}$
[-5 - 0]	$p\hat{E} + \frac{Q_{90}-2(\hat{\lambda^{\uparrow}}-\hat{\lambda^{\downarrow}})}{Load}$
[0 - 5]	$p\hat{E} + \frac{0.08}{Load^2}$
[5 - 10]	$\frac{\hat{\lambda^{\downarrow}}(W_{CLS}+0.24)}{Load}$
10 =<	0.00

Finally, in table IV we summarize the total revenues observed for each strategy in comparison to bidding with the referenced strategy presented in (9):

TABLE IV
SUMMARY OF REVENUE FOR EACH TRADING STRATEGY

Trading Strategy	Revenue (k€)	% of dif. w./ Reference Bidding
Bidding perfect hindsight	55.819	3.60%
Reference Bidding	53.878	0.00%
Strategy A (h)	54.771	1.66%
Strategy B (τ)	54.039	0.30%
Strategy C ($\hat{\lambda^{\uparrow}} - \hat{\lambda^{\downarrow}}$)	53.922	0.08%

As illustrated in the above table the data driven interpretable models, in the testing set, are performing well in comparison to the referenced analytical quantile strategy.

V. CONCLUSIONS

This paper proposes a novel way to produce interpretable data-driven models for solar power plant trading strategies. Such models are important for market players aiming at reducing their imbalance costs. In this context, we develop interpretable models through Genetic Programming (GP) and more precisely Symbolic Regression (SR). In the case study of trading the power produced by a solar photovoltaic (PV) power plant, we illustrate that the proposed model is able to perform as well as the reference analytical optimal bidding. Thus we can conclude that without compromising their accuracy, strategies obtained by SR introduce an interpretable analytical tool for decision makers.

Such models, based on data-driven approach of SR, could be replicated in other energy sector applications, such as wind farms, in order to investigate different strategies to optimize their bidding behaviour with interpretable models.

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REFERENCES

[1] SolarPower Europe. EU market outlook for solar power. 2021.

[2] A. Nespoli et al. Day-ahead photovoltaic forecasting: A comparison of the most effective techniques. *Energies 2019, Vol. 12, Page 1621*, 12:1621, 4 2019.

[3] V.S.B. Kurukuru et al. A review on artificial intelligence applications for grid-connected solar photovoltaic systems. *Energies 2021, Vol. 14, Page 4690*, 14:4690, 8 2021.

[4] A. Venzke et al. Verification of neural network behaviour: Formal guarantees for power system applications. *IEEE Transactions on Smart Grid*, 12:383–397, 10 2019.

[5] T. Carriere et al. An integrated approach for value-oriented energy forecasting and data-driven decision-making application to renewable energy trading. *IEEE Transactions on Smart Grid*, 10:6933–6944, 11 2019.

[6] A. C. Stratigakos et al. Prescriptive trees for integrated forecasting and optimization applied in trading of renewable energy. *IEEE Transactions on Power Systems*, 2022.

[7] A. Thampi. Interpretable AI building explainable machine learning systems, 2020.

[8] J.R. Koza. Genetic programming as a means for programming computers by natural selection. *Statistics and Computing*, 4:87–112, 1994.

[9] M. Du et al. Techniques for interpretable machine learning. *Communications of the ACM*, 63:68–77, 12 2019.

[10] C. Rudin. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1:206–215, 5 2019.

[11] A. A. Ismail et al. Benchmarking deep learning interpretability in time series predictions. *Advances in Neural Information Processing Systems*, 2020-December, 10 2020.

[12] M. Kommenda et al. Parameter identification for symbolic regression using nonlinear least squares. *Genetic Programming and Evolvable Machines*, 21:471–501, 9 2020.

[13] J. M. Morales et al. *Integrating Renewables in Electricity Markets*, volume 205. Springer US, 2014.