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Article

Application of machine learning tools for energy efficiency in industry: A review

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Review article

Application of machine learning tools for energy efficiency in industry: A review



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ABSTRACT

The current industrial context favors the generation of large amounts of data, most of which still seems to remain unexplored by the majority of enterprises. This paper presents a literature review on methodologies reported in the scientific literature exploring the potential value of industrial data via the utilization of Machine Learning tools for energy efficiency related goals. This work identifies and examines in detail the scientific contributions published up to date. A total of 42 published papers are found to present original contributions in this field, and addressing multiple energy efficiency challenges. A descriptive analysis is presented and demonstrates that the number of published works in this field is rapidly growing. The majority of contributions address challenges in petrochemical industries, and namely in ethylene production. There is still a very limited number of published papers addressing the application of Machine Learning tools on energy related objectives in other types of industries. The technical content of all identified papers is thoroughly reviewed and their key features and objectives are highlighted. A number of important themes across the final list of papers emerges, addressing challenges such as energy consumption forecast, energy analysis and energy optimization. A framework identifying the key goals reported on the set of 42 papers and the tools proposed to address them is suggested. This framework provides a summary on existing tools and facilitates the identification of research needs in this field. Additionally, the proposed framework serves as a reference guideline for the manufacturing and process industries on the selection of adequate Machine Learning tools for energy efficiency objectives via the utilization of industrial data.

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List of acronyms – error metrics

ARE	Average Relative Error
ARGE	Average Relative Generalization Error
ARMSE	Average Root Mean Squared Error
GRE	Generalized Relative Error
MAE	Mean Average Error
MAPE	Mean Average Percentage Error
MCC	Model Correlation Coefficient
MSE	Mean Squared Error
R ²	Coefficient of Determination
RGE	Relative Generalization Error
RMSE	Root Mean Squared Error
SD	Standard Deviation

List of acronyms – general

AI	Artificial Intelligence
BDP	Best Demonstrated Practices
EE	Energy Efficiency
EM	Energy Management
EMS	Energy Management Systems
EPI	Energy Performance Indicator
ISO	International Standard Organization
KPI	Key Performance Indicator
ML	Machine Learning

List of acronyms – tools

AHP	Analytic Hierarchy Process
ALAMO	Automated Learning of Algebraic Models for Optimization
ANFIS	Adaptive Network Fuzzy Inference System
ANN	Artificial Neural Network
AP	Affinity Propagation
BE	Backward Elimination
CC	Correlation Coefficient
CCR	Charnes–Cooper–Rhodes DEA model
CF	Cross Feature
DA	Discriminant Analysis
DEA	Data Envelopment Analysis
DEACM	DEA-cross model
DFA	Discriminant Function Analysis
ELM	Extreme Learning Machine
EMD	Empirical mode decomposition
FAHP	Fuzzy Analytic Hierarchy Process
FCM	Fuzzy C-Means
FIE	Fuzzy Inference Engine
FIS	Fuzzy Inference System

FLNN	Functional Link Neural Network
GA	Genetic algorithm
GOA	Genetic optimization algorithm
GP	Gaussian Process
HVVF	Hierarchical Variable Variance Fusion
I ² S	Intelligent Immune Systems
ICBR	Intelligent Case Based Reasoning
IDA	Index Decomposition Analysis
ISM	Interpretative Structural Model
JIT	Just In Time (Learning)
LSSVM	Least Squares Support Vector Machine
LSSVR	Least Squares Support Vector Regression
MAF	Moving Average Filter
MC	Monte Carlo
NIVSG	Nonlinear Interpolation Virtual Sample Generation
OLS	Ordinary Least Squares
PCA	Principal Components Analysis
PCR	Principal Components Regression
PLS	Partial Least Squares
PSO	Particle Swarm Optimization
QES	Quadratic Exponential Smoothing
RBFNN	Radial Basis Function Neural Network
SMI	Subspace Model Identification
SQP	Sequential Quadratic Programming
SVC	Support vector clustering
SVM	Support Vector Machines
SVR	Support Vector Regression
VPSO	Vibration Particle Swarm Optimization
VSG	Virtual Sample Generation

1. Introduction

A review on papers published over the last 20 years relating, directly or indirectly, to the broad field of energy management (EM) in industry shows that, almost without exception, all describe a pressing need for more effective ways to generate and utilize available energy resources (Bunse et al., 2011; Schulze et al., 2016). This is due to a growing consciousness on the potential dangers of human activity on the environment, and especially at a stage when the balance between human population, providing adequate living conditions for all, and diminishing natural resources raises important questions and challenges.

As a result, the number of scientific papers related to EM in industry has been increasing and contributing with a myriad of new developments in the field (Schulze et al., 2016; May et al.,

2017). This has been further stimulated by governments worldwide recognizing the importance of energy efficiency (EE) and launching a variety of initiatives such as the Energy Star program (US) (Energy Star, 1992), the 2020 climate & energy package (EU) (European Commission, 2009), China's 13th Five Year Plan For Economic and Social Development (China) (Communist Party of China, 2016) and others, each focusing on a specific geographic context.

While the current context is favorable to the development of energy efficient processes, there is still a generalized lack of awareness, knowledge and experience in the industry on how to implement these concepts (Prashar, 2017; Thollander and Palm, 2015). Industrial priorities are usually set towards more immediate objectives, and EE is seldom one of the most important priorities set out by enterprises (Sorrell, 2015; Reddy, 2013).

One of the most important challenges for the manufacturing and process industries in this context is how to explore the potential of recorded data. The amount of data is growing rapidly across industry, owing to the widespread availability of cheap sensors, and the need for improved process monitoring and reporting (Diez-Olivan et al., 2019; Shang and You, 2019). The accumulation of large volumes of data presents huge opportunities for all activity sectors, and as a result, enterprises are increasingly turning their attention to Machine Learning (ML) tools as a path to explore its potential. The dawn of Industry 4.0 and Artificial Intelligence (AI) in particular has brought a renewed interest in ML tools, and there is currently a great drive across all industries to explore its potential (Alcácer and Cruz-Machado, 2019; Lu, 2017).

ML includes a variety of powerful tools (Bishop, 2006; Goodfellow et al., 2016) facilitating the extraction of valuable insights from raw data (e.g. class prediction, pattern recognition), which can then be used to assist enterprises improve their operations and strategic decisions.

This paper explores the utilization of ML tools in the manufacturing and process industries for EE goals, by examining relevant works published in the scientific literature up to date. Through a detailed literature search, it is the goal of this contribution to present a state-of-the-art review on how ML tools have been used to explore the value of data and address key issues relating to industrial EE and EM. In particular, the following research objectives are identified:

- **Research objective 1:** Identify relevant scientific articles addressing the subject of EE in industry through the use of ML tools (Section 4.1);
- **Research objective 2:** Capture research interest in this area and identify trends and key applications (Section 4.2);
- **Research objective 3:** Describe strategies using ML tools for EE related challenges in industry (Section 4.3);
- **Research objective 4:** Explain how these tools are used to derive meaningful insights for EE problems (Section 4.3);
- **Research objective 5:** Identify patterns in the current research and establish a framework and guidelines for application of ML tools on EE problems by the manufacturing and process industries (Section 5.1);
- **Research objective 6:** Identify open challenges and trends in the current research (Section 5.2).

This paper aims to be a reference for both academia and industry. On one hand, it aims to identify the strategies already in place and the gaps in the literature, and thus paving the way for new academic contributions in the field. On the other hand, it aims to provide an outlook for industry on the features of each contribution for a clear assessment on the potential benefits of its utilization in a specific industrial context.

The rest of the paper is organized as follows: in Section 2, relevant works on industrial EE are presented. Section 3 describes the proposed literature review methodology. The literature search results are presented in Section 4 and discussed in Section 5, where a framework for the utilization of ML tools on industrial EE is suggested. At last, the conclusions of this work are presented in Section 6.

2. Literature review

2.1. Energy efficiency in industry

Until the 1970s, the subject of EM in industry was given minimal attention (Petrecca, 2014). The turning points were the oil crisis during the 1970s, which lead to concerns on energy security, and thus strongly promoting more energy efficient technologies and operations (Kaya and Keyes, 1980). The present panorama on energy utilization is significantly different from the early 1970s. The mindset towards energy utilization is changing and increasingly aiming at eliminating unnecessary losses and inefficiencies, and driven by both economic and environmental reasons (Johansson and Thollander, 2018; Marimon and Casadesús, 2017; Thollander and Ottosson, 2010).

The scientific community has been actively involved in addressing these issues, and as a result, the literature on the subject is extensive, and addressing a plethora of topics related to industrial EE (Schulze et al., 2016; May et al., 2017). This is intrinsically a multidisciplinary field (Sorrell, 2015), and thus encompassing contributions from a purely technical point of view, to contributions focusing on social or economic aspects. The development of adequate EE key performance indicators (KPIs), for instance, is of paramount importance to capture and track performance and improvements, and a large range of KPIs have been reported in the literature (Bunse et al., 2011; Benedetti et al., 2017). All these EE indicators express a ratio between a *delivered useful output* and a form of *required energy input*, fundamental to the concept of energy efficiency.

An extensive review of all contributions in the field of industrial EM is beyond the scope of this paper. However, it is worth pointing to some of the works focusing mostly on *technical* functions for industrial EE and in line with the goals of this paper. This includes, for instance, the works presented in Carpenter et al. (2018), Pelser et al. (2018) and Ke et al. (2013), focusing on the utilization of benchmark and baseline methods. A variety of management strategies for promoting EE has been reported and including multiple contributions as presented in Trianni et al. (2019) and Porzio et al. (2013). Several contributions address the implementation and effectiveness of energy audits in industry (Fresner et al., 2017; Backlund and Thollander, 2015; Kabir et al., 2010). In Zeng et al. (2018), Gahm et al. (2016) and Biel and Glock (2016), the authors explore the potential of scheduling and production planning in industry for improved EE. Mawson and Hughes (2019) and Zhou et al. (2016) explore the potential of modeling techniques for EE goals. Modeling further enables the development of optimization-based techniques (Frangopoulos, 2018; Cui et al., 2017), or the development of predictive methods (Liao et al., 2018). Other topics of interest in this field include, for instance, fault diagnostics (Yao et al., 2016), and EM from the micro to the macro levels (Mancarella, 2014; Duflo et al., 2012).

There is also a significant body of literature focusing on less technical themes, but rather on the *context* around the implementation of EE measures. This includes, for instance, energy policies (Malinauskaitė et al., 2019; Palm and Thollander, 2010), barriers and drivers for EE (Sorrell, 2015; Andersson and Thollander, 2019; Thollander et al., 2013), technology adoption rates (Hanes

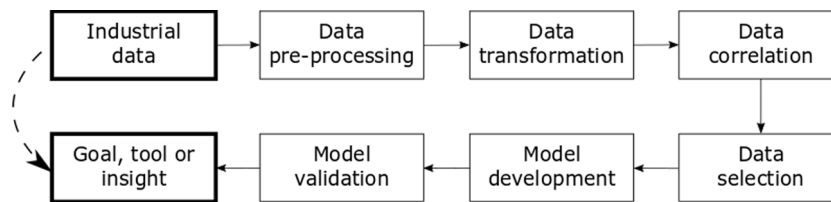


Fig. 1. Typical steps used for insight extraction from data via ML tools.

et al., 2019), maturity profiles and adoption rates (Trianni et al., 2019; Jovanović and Filipović, 2016), attitudes towards EM and assessment of EE practices (Trianni et al., 2019; Dobes, 2013) or the need for improving EE standards and tools to assist standards implementation (Gonçalves and dos Santos, 2019; Gopalakrishnan et al., 2014).

The introduction of the ISO 50001 standard in 2011 (International Organization for Standardization (ISO), 2018) has been an important step for EM, and providing a framework for the implementation of Energy Management Systems (EMS) in industry. This has further prompted research in this field and the development of frameworks to capture the distinct and complementary aspects to its implementation highlighted in the two previous paragraphs. Bunse et al. (2011) proposes a top-level architecture of themes for EMS, including: (i) Measurement, (ii) Control and Improvement, and (iii) Enablers. May et al. (2017) suggests a more refined framework including 6 themes: (i) Drivers and Barriers, (ii) Information and Communication Technologies, (iii) Strategic Paradigms, (iv) Supporting Tools and Methods, (v) Manufacturing Process Paradigms, and (vi) Manufacturing Performances. There are currently several contributions in this field, including for instance those reported in Bunse et al. (2011), Schulze et al. (2016), May et al. (2017), Lee and Cheng (2016), Sucic et al. (2016), Hall and Buckley (2016), Olanrewaju and Jimoh (2014), Peng and Xu (2014), Drumm et al. (2013), Rudberg et al. (2013) and Abdelaziz et al. (2011).

These frameworks cover a variety of subjects, but none focuses specifically on the utilization of ML methods to capture the potential of industrial data for EE related goals. To the best of the authors' knowledge there are no papers in the scientific literature providing a review on this subject. The present work is thus proposed as an extension of the conceptual frameworks reported for EMS, and with a specific focus on the utilization of ML tools for EE goals.

2.2. Machine learning overview

ML encompasses a wide range of tools for insight extraction from data. This includes Artificial Neural Networks (ANN), Support Vector Machines (SVM), Clustering techniques, Principal Component Analysis (PCA) and many others. A detailed review of ML is beyond the scope of this paper, and excellent reviews on the subject may be found in Bishop (2006), Goodfellow et al. (2016) and Raschka and Mirjalili (2017).

However, it is convenient to introduce a formal architecture for the utilization of ML tools. The problem of generating insights from data is often not a trivial one, and in fact requiring that a number of steps are utilized to sequentially transform raw data and obtain increasingly richer information. Fig. 1 illustrates a typical *data workflow* for insight generation.

This workflow is merely a guideline and adapted from Goodfellow et al. (2016) and Raschka and Mirjalili (2017). In fact, each ML problem typically requires a customized set of steps, depending on the data available and objectives defined. This general architecture is offered as a reference, and the literature review undertaken in this contribution will seek to assess which of these steps are used in each contribution, their exact order and which tools are used for each step.

3. Research methodology

Literature reviews are an essential part of any scientific contribution. They provide the key background and motivation for any such contribution, by pointing out related works in a research field, as well as the limitations in the existing literature to adequately frame the need for the proposed developments.

While all research papers include a literature review section, review papers such as the present case focus specifically on a detailed literature review exercise. The main contribution of review papers is offering a detailed assessment on the state-of-the-art of any research field of interest, and enabling a critical review of the latest developments, trends, outstanding issues and research needs, as well as the development of general frameworks, whereby papers are categorized according to some predefined criteria (Tranfield et al., 2000).

Research papers are usually not subject to any predefined requirements concerning literature review. They reflect the author's knowledge in the field and should ideally provide a fair assessment of the state-of-the-art contributions. In review papers, however, a more scientific approach towards literature review is recommended, and extending beyond the authors' knowledge of the field. This ensures that literature reviews are: (i) impartial, (ii) reproducible and (iii) comprehensive, and that the review includes *all* relevant contributions from *all* backgrounds, and not limited to the authors' prior knowledge or predefined conceptions of the research field.

The proposed literature review is adapted from Tranfield et al. (2000) and Mayring (2000) for identifying papers and collecting evidence from their contents in a systematic way. The proposed architecture for this literature review is presented in Fig. 2, and each step presented in sequence.

3.1. Search keywords definition

The first step defines the scope: only scientific papers making use of the following three concepts *simultaneously* are relevant to this literature review:

- Energy Efficiency;
- Manufacturing and Process Industries;
- Machine Learning.

While devising the ideal structure for the literature search, and maximizing the number of found relevant contributions, several combinations of keywords were tested in Science Direct' search engine. It was concluded that using only the keywords above was very restricting. This is due to the fact that a number of relevant contributions actually do not place the emphasis on "efficiency", but rather on "saving". Or, instead of identifying "industry" as a keyword, place the focus on "production".

These early observations illustrated how difficult it is to capture all relevant works in the field, and, additionally, provided the necessary insight to refine and expand the original set of search keywords. Energy is one of the key focus of this literature search, and "energy" has therefore been selected as the *basic* search

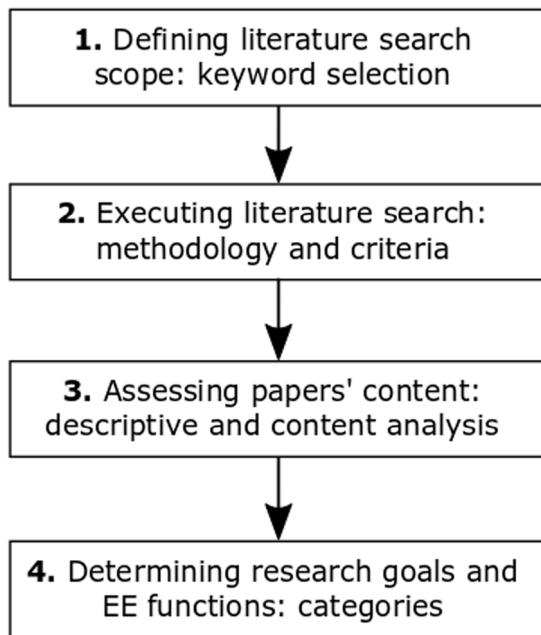


Fig. 2. Literature search strategy.

Table 1
Goal search keywords.

Efficiency	Analysis	Consumption	Saving
Management	Optimization	Model	Diagnosis
Prediction	Evaluation	Baseline	Classification

Table 2
Context search keywords.

Industry	Process	Manufacturing
Plant	Factory	Production
System	Case study	Application

Table 3
Tools search keywords.

Machine learning	Neural network
Fuzzy logic	Artificial intelligence

keyword. The three general topics identified above actually correspond to three characteristics of the papers of interest: “Energy efficiency” represents the *goal* of the papers, “Manufacturing and Process Industries” represents the *context* and “Machine Learning” stands for the group of *tools* used. Therefore, for a more comprehensive literature search, a number of keywords were defined within each of the topics: (i) goal, (ii) context, and (iii) tools. These keywords are listed in Tables 1–3.

While this approach results unavoidably in a much larger number of papers to assess, it is also expected to return a larger set of relevant research papers, and thus enabling a more comprehensive assessment of this research field.

3.2. Acceptance criteria and search workflow

This step concerns the actual search activity. The literature search was performed using Science Direct’ search engine, and was restricted to return only review articles and research articles. Scopus was also used to check cross referenced material. The search was actually broken down in 18 literature searches to avoid using – simultaneously – the full set of 25 keywords listed in Tables 1–3; given the search engine’s architecture this is in fact

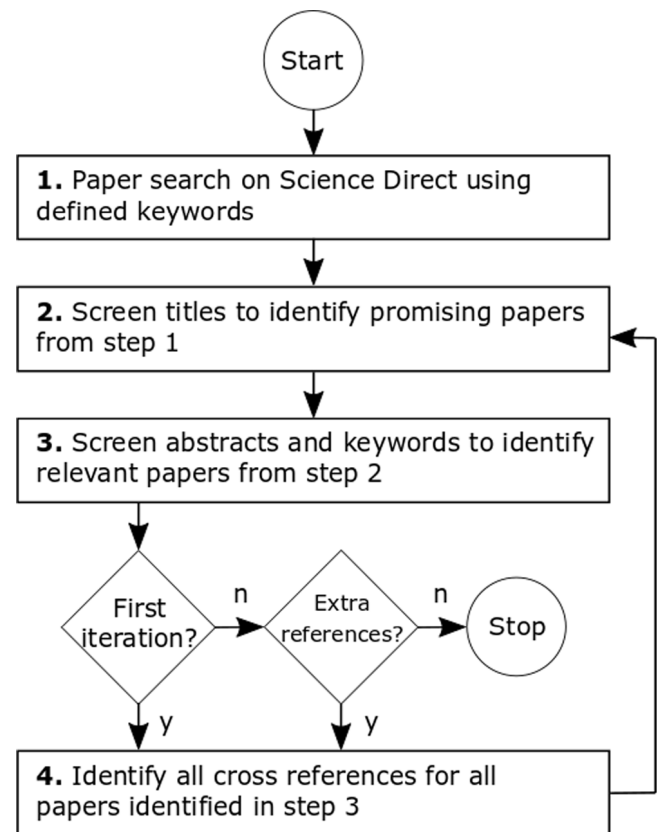


Fig. 3. Methodology used for identification of relevant papers.

not feasible, and thus requiring complementary searches to cover all possible keywords combinations.

A number of screening and cross-reference checking steps were introduced to identify relevant papers. The screening methodology is schematically described in Fig. 3.

Upon completion of the keyword search (step 1 in Fig. 3), all article’s titles identified by the search are read (step 2), and only those suggesting a relevant contribution in line with the search objectives are kept. The remaining articles are excluded from further analysis. In step 3, all abstracts and keywords for all papers identified in step 2 are read, to determine more precisely the significance and contents of each contribution. Only those articles reporting the use of at least one ML tool to process industrial data for some EE related goal are added to the list of relevant articles. The remaining articles are excluded from the search. This completes the first iteration.

To minimize the risk of not identifying relevant contributions, step 4 focuses on screening cross-references. This includes both citations to and from papers identified in step 3. Each of these extra papers goes through the same screening strategy (steps 2 and 3) to identify relevant, and previously unidentified papers. Steps 2–4 are repeated as many times as necessary until all new papers identified in step 3 include no new cross-references to previously unidentified contributions, thus concluding the identification of relevant contributions.

3.3. Descriptive and content analysis

In step 3 of the proposed literature search (Fig. 2), all papers identified in step 2 are carefully read. This assessment step includes two complementary parts. Firstly, the key features of each contribution are extracted. This provides the key ingredients for a *descriptive analysis* and including the following information:

Table 4
Distribution of papers per scientific Journals.

Energy	14	Computers & Chemical Engineering	1
Journal of Cleaner Production	6	Industrial & Engineering Chemistry Research	1
Energy Conversion and Management	5	IEEE Transactions on Systems, Man, and Cybernetics: Systems	1
Applied Energy	4	Journal of Analytical and Applied Pyrolysis	1
Applied Thermal Engineering	3	Measurement	1
Expert Systems with Applications	2	Advanced Engineering Informatics	1
International Journal of Energy Research	2		

- Publication Years;
- Journals;
- Geographic contexts;
- Industry types.

The second part, a full *content analysis*, aims to extract specific technical details on each contribution, namely which ML tools are used and how they are used for EE goals.

3.4. Article categories and EE functions

After technical screening, common themes among the full list of papers are identified (step 4). Results are presented separately under each of the identified categories to evidence this structure of themes. In Section 5, a critical review of all relevant papers is conducted, and focusing on all the identified technical functions for EE, and thus delivering a comprehensive framework of contributions and available tools in the field.

4. Results

4.1. Literature search

Fig. 4 summarizes the results from the search stage. A final redundancy check was made to ensure there are no repeated references emerging from different individual searches. Abstract and keywords screening, and a single cross referencing round resulted in a total of 42 relevant papers.

4.2. Descriptive analysis

4.2.1. Publication years

Fig. 5 captures the distribution of identified papers per year. It demonstrates that there has been an increased interest on these topics over the last 10 years. In particular, there has been a sharp increase in the number of related publications in 2017 and 2018. The results for 2020 still do not reflect the real figures for this year, as the literature review only includes papers published or in press up to the end of March 2020.

4.2.2. Journals

Journal “Energy” is the most widely used for publication of contributions in this field, including one third of all publications. A total of 13 journals include all identified works. As expected, these journals tend to be focused on technical applications in the field of Energy. Table 4, presents the breakdown of publications per journal.

4.2.3. Geographic contexts

China is the undisputed leader of contributions. This is not surprising given the fact that China is presently the largest energy consumer in the World and that its industry represents a very significant share of total energy consumption (International Energy Agency (IEA), 2018; Enerdata, 2019), thus providing a very favorable context for EE developments. There are a total of 7 contributions from Europe, 5 contributions using data from an unidentified geographical source and another contribution working with emulated data. These results are summarized in Table 5.

Table 5
Distribution of papers per geographic context.

China	29
Europe	7
Not specified	5
Emulated data	1

Table 6
Distribution of papers per industry type.

Ethylene	19	Propylene oxide	1
Ethylene & PTA	8	Carbon fiber production	1
Machining processes	2	Cement	1
Additive manufacturing	2	Clothing industry	1
PTA	1	Turbine condenser air extraction system	1
Naphtha reforming	1	Steel plant	1
Petrochemical plant	1	Components	1
HDPE & PTA	1		

4.2.4. Industry types

Ethylene, and the petrochemical industry, is the main focus of research activities as shown in Table 6. These figures track closely the number of publications originating from China and highlight the huge effort Chinese researchers are devoting to energy optimization of the petrochemical industry. A collection of works in nine other industry types was also identified, though including a limited number of contributions.

4.3. Content analysis

The contents of all papers were firstly assessed, and then general themes in the literature were identified based on the common features of this group of papers, using the inductive approach presented in Mayring (2000). The categories identified capture the key goals towards EE found in the group of 42 papers, as listed below:

- EE Ranking and Analysis;
- EE Analysis;
- Production Forecast and EE analysis;
- Energy Consumption Forecast;
- Energy Consumption Optimization;
- Technology and Scale for EE;
- EE Multi-objectives.

All papers were assigned to a single category and results are reported on two distinct levels. Firstly, a general overview of all categories is presented in the following subsections, and highlighting specific contributions in each category. Then, the key technical features of all contributions are summarized in Tables 7–13, one table per each of the categories presented above. Two important pieces of information are presented in these set of tables:

- ML tools and other relevant tools used in each contribution, and the data workflows used for information extraction;
- Tools, metrics or useful insights for the purpose of industrial EM.

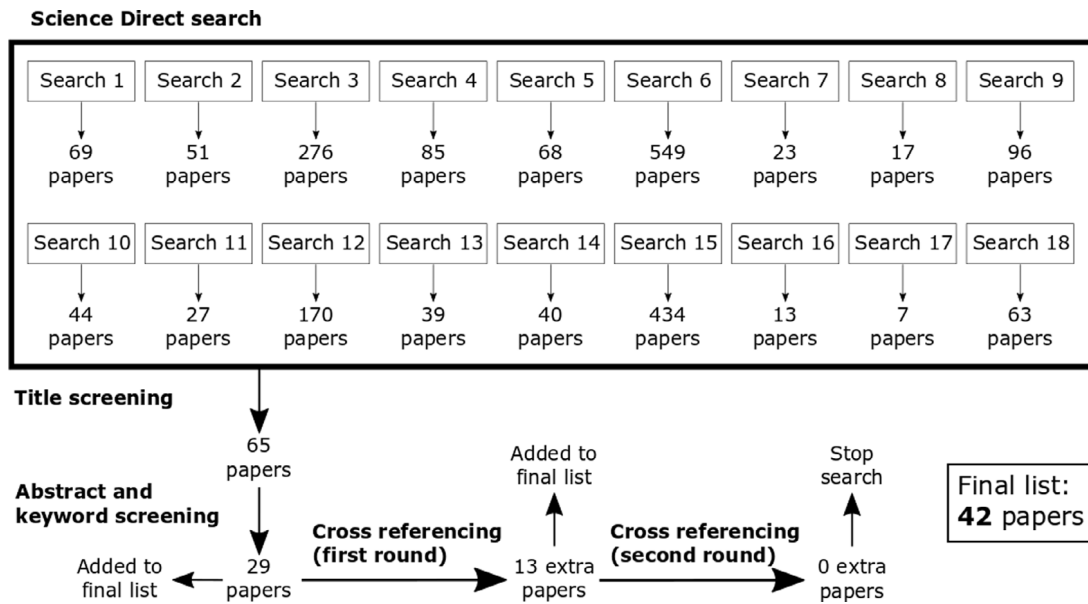


Fig. 4. Literature review screening results.

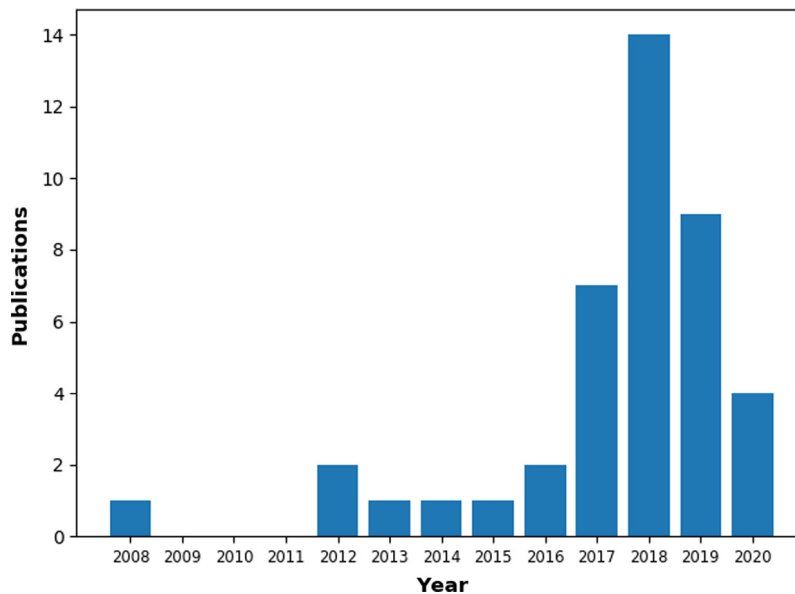


Fig. 5. Distribution of papers per year.

4.3.1. EE ranking and analysis

The contributions in this group fall also on the very broad group of papers utilizing Data Envelopment Analysis (DEA) tools (Cooper et al., 2007) for the purpose of EE assessments. One of the key difficulties with this group of tools is to provide a clear meaning to the efficiency indexes obtained as a result of their application, and how to select adequately data for meaningful DEA studies capturing EE. A large range of variables may often be available, but only a few may be significant for the EE problem. The literature on this subject is extensive, and in the specific context where ML provide extra insights into this challenge, two papers were identified (Geng et al., 2019b; Han et al., 2019b). Both work on a similar principle, and use Affinity Propagation (AP) for a more focused selection of input variables. While there are differences between the two, generally, both aim at providing greater resolution power to the DEA analysis.

4.3.2. EE analysis

Relevant contributions in this category are diversified, both concerning the set-up of a modeling approach, as well as the type of EE objectives defined. Beisheim et al. (2019) suggests a very comprehensive framework for the utilization of industrial data for EE related goals. In Zhu et al. (2018) an ANN model is used to enable the prediction of an EE level as a function of process inputs. The utilization of fuzzy logic is a trend in this type of contributions; it enables a more structured energy analysis in face of the problem of measurement uncertainty. Gong et al. (2017b) provides a framework for identification of key patterns in energy utilization, and targets the identification of variables with highest impact on EE. A common theme across these papers is the identification of improved process inputs for optimal EE.

4.3.3. Production forecast and EE analysis

All papers in this category share the same basic strategy: they focus on the utilization of a neural network model to forecast

Table 7Key paper contents on *EE Ranking and Analysis*.

Reference	Tools and data workflows	EE insights
Geng et al. (2019b)	Transformation: Data normalization. Selection: AP algorithm to filter non-critical and redundant information. Model: Charnes–Cooper–Rhodes (CCR) DEA model to build EE model.	<ul style="list-style-type: none"> ● AP improves ranking resolution power of DEA tools. ● CCR model requires data from multiple units. ● Calculation of relative EE metrics, ranking of units and identifying potentials for improvement.
Han et al. (2019b)	Pre-processing: Data normalization. Selection: AP algorithm to filter non-critical and redundant information. Model: DEA-cross model (DEACM) to build EE model.	<ul style="list-style-type: none"> ● DEACM model provides greater ranking power than classic DEA tools. ● Data taken from multiple units. ● Enables analysis of units' performance, via comparison against benchmark and assessment of potentials for plant performance improvement.

Table 8Key paper contents on *EE Analysis*.

Reference	Tools and data workflows	EE insights
Beisheim et al. (2019)	Pre-processing: Outlier removal and data classification. Transformation: Data centering and scaling. Selection I: Clustering with <i>k-means++</i> to select representative points and identify characteristic points for operation. Model: Surrogate model with <i>Automated Learning of Algebraic Models for Optimization</i> (ALAMO) software package. Selection II: A final Backward Elimination (BE) step is applied to identify the most important factors on plant performance.	<ul style="list-style-type: none"> ● Focus on identifying Best Demonstrated Practices (BDP) for different operating regimes as baselines for efficiency assessment. ● Group of data points among the top percentiles (according to some predefined Energy Performance Indicator (EPI)) identified as BDP. ● Enables online tool to assess EE in operation against BDP, and under similar operating conditions. ● Insights on most important factors for driving process towards BDP.
Zhu et al. (2018)	Transformation I: EPI calculated from input and output data variables using a variable fusion approach. Transformation II: Input data normalization. Transformation III: Data fuzzification using Mamdani type <i>Fuzzy Inference System</i> (FIS) as “low”, “median” and “high”. Model I: <i>ELM-FIS</i> model predicts membership of each of the three defined EE levels as a function of process inputs. Model II: DEA with process inputs and outputs. Validation: Validation against other ANN schemes. Calculation of Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2).	<ul style="list-style-type: none"> ● EPI is a tailored EE metric. ● Predicts EE of any given operating point in one of the three levels. ● Subsequent DEA calculations enables energy saving opportunities and directions for improvement.
Geng et al. (2018a)	Transformation: Data converted to <i>fuzzy</i> equivalent. Correlation/Model: Correlation via Interpretative Structural Model (ISM). Three scenarios defined using fuzzy logic to quantify energy consumption inputs: “minimum”, “most likely” and “maximum”.	<ul style="list-style-type: none"> ● Correlations based on ISM to identify most relevant process inputs. ● Comparing curves for each of the three scenarios as the key elements for energy related insights: “Most likely” and “maximum” scenarios used to quantify energy saving potentials. ● Useful for systems subject to measurement uncertainty.
Gong et al. (2017b)	Pre-processing: Data consistency test (Grubbs test). Correlation: Most significant variables for energy consumption determined via <i>Principal Components Regression</i> (PCR). Selection: Classes defined for each of the key process variables, and dataset grouped into each of the available classes, via <i>k-means</i> . Model: EE calculated via DEA tools within each identified class.	<ul style="list-style-type: none"> ● Cluster analyses enables the identification of several modes of operation. ● EE analysis takes into account the influence of key operating variables. ● By clustering data in groups of reference operating conditions, EE is put in a specific context, making such assessments more precise and fair. ● Clues for process optimization via DEA slacks.
Han et al. (2015)	Pre-processing: Data consistency test (Grubbs test). Transformation: Data <i>fuzzified</i> in three levels: “well”, “median” and “bad”. Model: DEACM for EE calculation using fuzzified inputs and outputs.	<ul style="list-style-type: none"> ● Takes data from several units and from different years of operation. ● DEACM slacks to analyze performance in greater detail and identify possible improvements with respect to most effective units. ● Based on a graphical analysis for the three identified scenarios/levels.

some industrial key output. The Extreme Learning Machine (ELM) architecture is the most common ANN choice, while specific details for setting the architecture parameters and finding the function parameters vary. The predicted output is in most cases industrial production.

While all ANN architectures are set up to achieve similar goals, there are many variations to their specific set-ups, and particularly: (i) which input variables to select, and, (ii) which data to feed the ANN for model training. This is the key difference observed across this group of papers and resulting in a considerable set of approaches to deal with these challenges. Two papers (He et al., 2018; Gong et al., 2017a) also focus on the generation

of virtual samples, when data available is deemed insufficient for accuracy.

This group of papers explains in detail both the tools used and how to combine them to achieve the defined goals, but generally provide limited information on how the developed models are used for EE related challenges. Generally, they provide a view on EE, which does not necessarily focus on the utilization of standard EE metrics, but rather, on providing a richer insight based on saving potentials and directions for improvement. This is achieved via comparison and benchmarking, and using predicted and experimental results – typically in the form of graphs – for extracting relevant insights.

Table 9

Key paper contents on *Production Forecast and EE Analysis*.

Reference	Tools and data workflows	EE insights
Geng et al. (2020)	<p>Pre-processing: Outliers removal.</p> <p>Transformation: Data normalization. New dataset created via Cartesian Product under the Cross Feature (CF) method.</p> <p>Model: Input matrix constructed in a convenient format to satisfy the requirements of the <i>Convolutional Neural Network</i> and model learning using input and output data.</p> <p>Validation: Data divided in training and testing datasets. Relative Generalization Error (RGE) and Average Relative Generalization Error (ARGE) calculation.</p>	<ul style="list-style-type: none"> ● Method applied to ethylene plant, taking crude oil, fuel, steam, water and electricity and output is ethylene production. ● Indirect EE assessment based on graphical analysis of data and comparisons between predicted and actual plant data. ● Insights for EE improvement based on comparisons between distinct operating points.
Han et al. (2019c)	<p>Transformation: AP algorithm identifies clusters in original dataset, capturing its variability in a compact form.</p> <p>Model: ELM used to build model, using the clusters from the previous step.</p> <p>Validation: Data split in training and test sets. Calculation of error metrics.</p>	<ul style="list-style-type: none"> ● Concept of improved plant suggested. Few details presented on this concept, and results suggest it derives from further simulation activities using developed model and comparisons against benchmark points. ● Works on historical data to capture the potential for improvement on each data point, therefore providing a path for capturing EE without utilizing a formal EE indicator.
Han et al. (2019a)	<p>Transformation I: Data normalization. Data transformed in a convenient format for modeling step.</p> <p>Model: <i>Recurrent Neural Network</i> with Long Short Term Memory and Attention Mechanism modules to predict production.</p> <p>Validation: Comparison of actual and expect output to calculate error metrics: ARGE and RMSE. Data split in training and test sets.</p>	<ul style="list-style-type: none"> ● EE insights from comparisons between plant data and model predictions. ● Comparison of performance between different time samples to obtain insights into how EE may be improved.
Geng et al. (2018c)	<p>Correlation: Pairs of process variables assessed via ISM.</p> <p>Transformation/Selection: Small set of variables fused via Analytic Hierarchy Process (AHP).</p> <p>Model: Prediction of plant production using ELM neural networks.</p> <p>Validation: Computation of Mean Squared Error (MSE). Data split in training and test sets.</p>	<ul style="list-style-type: none"> ● Prediction model for plant production. ● EE is captured qualitatively by comparison of real and predicted production. ● Suggests a route for energy analysis and process performance optimization via comparison of real and predicted points.
He et al. (2018)	<p>Transformation: Data normalization.</p> <p>Correlation: <i>Nonlinear Interpolation Virtual Sample Generation</i> (NIVSG) to interpolate on dataset points to generate new virtual data points.</p> <p>Model: ELM neural network used to train model using original and virtual data points from NIVSG.</p> <p>Validation: Mean Average Percentage Error (MAPE) computed to check accuracy of prediction model. Data split in training and test sets.</p>	<ul style="list-style-type: none"> ● Model enables prediction of production as a function of key process inputs. ● NIVSG algorithm promotes accuracy of prediction. This technique is useful for small datasets. ● Strategy for EE based on comparison of a group of plants operating in the same industry, and identifying the most efficient as reference for less efficient units.
Geng et al. (2018b)	<p>Selection: Five key process inputs selected for model development based on experience.</p> <p>Transformation: Data normalization.</p> <p>Model: Prediction model for production based on ELM structure. Model trained using historical data.</p> <p>Validation: Model error with ARGE.</p>	<ul style="list-style-type: none"> ● Data gathered from multiple ethylene manufacturing units. ● EE studies based on comparison of distinct data points to provide a relative assessment on EE and potentials for improvement. ● Two types of EE studies performed: "same scale, different technologies", and "same technology, different scale". ● Contribution also relevant for category "Technology and Scale".
Han et al. (2018)	<p>Transformation: Data series fuzzified along time axis.</p> <p>Pre-processing: Data consistency using Grubbs test.</p> <p>Selection: Data divided in three performance categories: "worst", "median" and "optimal".</p> <p>Model: Production prediction for each of the three performance scenarios using <i>Fuzzy Extreme Learning Machine</i> neural network.</p> <p>Validation: Data split in training and test sets. Model error with ARGE.</p>	<ul style="list-style-type: none"> ● Predictive capability for plant production. ● EE inferred by comparison of worst, median and optimal performance curves. ● Energy analysis is also possible by comparison of energy figures associated with the identified scenarios.
Geng et al. (2017b)	<p>Transformations: Data clustering based on degree of similarity using <i>Fuzzy C-means</i> (FCM)</p> <p>Selection: Inputs in each cluster are fused to create a single representative variable per cluster using AHP.</p> <p>Model: ELM to predict production as a function of selected variables.</p> <p>Validation: Data split in training and test sets. ARGE and RMSE for model prediction accuracy check.</p>	<ul style="list-style-type: none"> ● EE analysis and energy saving potential obtained indirectly via comparison of predicted results against measurements, or by comparison between two units.
Geng et al. (2017c)	<p>Transformation: Data used to calculate activity, structure and intensity using Index Decomposition Analysis (IDA).</p> <p>Model: ELM uses outputs from transformation step as inputs to predict total production.</p> <p>Validation: Generalized Relative Error (GRE) for model accuracy check. Data split in training and test sets.</p>	<ul style="list-style-type: none"> ● EE obtained indirectly through graphical analysis of results. ● Enables energy analysis as a function of activity, structure and density.

(continued on next page)

4.3.4. Energy consumption forecast

There are few variations on the objectives of the contributions assessed. Most of them focus on deriving a predictive model for energy consumption as a function of process inputs. The only exception is Liu et al. (2019) which focuses on future prediction

of consumption based on recent energy consumption trends. Kovačič and Šarler (2014) also integrates the concepts of production plan and thus allowing for some scheduling based opportunities for energy optimization.

The frameworks used to achieve the objectives identified are diversified: not only ANN based models are used, but also signal

Table 9 (continued).

Reference	Tools and data workflows	EE insights
Han et al. (2017b)	<p>Pre-processing: Data consistency with Grubbs test.</p> <p>Transformation: Data normalization.</p> <p>Correlation/Selection: Correlation between pairs of variables using ISM and selection of reduced set of variables for model development.</p> <p>Model: Production prediction using <i>ELM</i>.</p> <p>Validation: ARGE and RMSE for model accuracy check. Data split in training and test sets.</p>	<ul style="list-style-type: none"> ● ISM reduces set of inputs and facilitates energy analysis. ● EE inferred by comparison of real and estimated production values. ● Qualitative comparison and analysis possible by comparison of two units operating in similar conditions.
Geng et al. (2017a)	<p>Transformation: Data normalization.</p> <p>Selection/Transformation: <i>Principal Components Analysis (PCA)</i> to transform original data, and restricted subset of principal components used for further modeling activities.</p> <p>Model: Prediction model for total production, based on <i>Radial Basis Function Neural Network (RBFNN)</i> structure. <i>FCM</i> used to set architecture parameters of RBF neural network.</p> <p>Validation: Data split in training and test sets. ARGE, RGE, MSE and RMSE error criteria used for accuracy assessment.</p>	<ul style="list-style-type: none"> ● EE and analysis results from a set of comparisons. Details on analysis framework developed are scarce. ● No formal metric for EE provided. Insight on the subject is derived purely on comparisons between data points.
Gong et al. (2017a)	<p>Correlation: Virtual Sample Generation (VSG), using Monte Carlo (MC) and Particle Swarm Optimization (PSO). Utilizes available data points to infer new points for model training.</p> <p>Model: Prediction model for feedstock consumption, using <i>ELM</i>.</p> <p>Validation: Data split in training and test sets. MAPE for accuracy assessment.</p>	<ul style="list-style-type: none"> ● EE analyses via comparison of predicted and actual plant data. ● Best performing units identified as benchmark. EE analysis for optimized performance based on comparisons against benchmark.
Han et al. (2016)	<p>Pre-processing: Data consistency (Grubbs test).</p> <p>Selection: All process energy inputs and main production outputs selected as the main variables of interest.</p> <p>Model I: C^2WH – DEA model used to assess efficiency scores and slack variables for a group of decision units.</p> <p>Model II: Efficient units and projection of inefficient units on efficiency frontier used as input for prediction of production using <i>Back Propagation neural networks</i>.</p> <p>Validation: ARGE and RMSE for accuracy checks. Data split in training and test sets.</p>	<ul style="list-style-type: none"> ● EE inferred by comparison of real and estimated production values. ● Qualitative comparison and analysis also possible by comparison of two units operating in similar conditions. ● Slacks of DEA used for providing clues on opportunities for process optimization.

processing, genetic algorithms and Least Squares Support Vector Machine (LSSVM). One of the key drivers for this type of estimation resides in the need for matching as closely as possible energy supply and demand.

4.3.5. Energy consumption optimization

The majority of contributions in this category focus mainly on defining and solving an optimization problem. The result is a set of optimal inputs for improving EE. The exception to this pattern is Monedero et al. (2012) where optimization focuses on searching a database of historical points to find a neighbor point to the current operation point for improving performance. All approaches use a modeling step to capture system behavior, and including a variety of ML tools. The obtained optimal solutions focus also on different paths for optimal EE. Wang et al. (2018) and Liang et al. (2018) aim to obtain optimized schedule settings, and therefore maximizing the utilization of available resources, where Golkarnareji et al. (2018) focus on updates to input variables of continuous processes.

4.3.6. Technology and scale for EE

In this set of contributions, production extension is identified as a key factor on EE. To capture its impact, a set of data fusion tools are proposed to obtain representative EE metrics for a number of technology/scale pairs. The obtained results provide good insight for technology selection based on EE criteria. Strušnik et al. (2016) suggests an alternative approach: pilot plant data are processed to develop input–output models, which are then used to create a reference operation scenario and identify the most promising technology.

4.3.7. EE multi-objectives

To some extent, all contributions assessed in the previous sections do provide insight into more than one energy related challenge. For instance, the result of a contribution focusing mostly on optimization may offer useful elements for energy analysis. The

distinction between the previous categories and this category is that the contributions in the present category do not necessarily focus on a single feature, but provide key results on at least two different types of objectives.

Unlike the previous categories, there are a significant variety of tools, workflows and objectives in the present group of contributions. They address several challenges in EM, including definition of adequate EE metrics, prediction, analysis and optimization, with ties to the groups previously identified. Most of the contributions in this group present an optimization feature, including either a formal mathematical optimization framework, or a qualitative insight extraction approach for process control.

5. Framework for utilization of ML tools on EE related problems in industry

5.1. Framework

In this chapter, results from Section 4 are presented from a different perspective: firstly, the contents of Tables 7–13 are reviewed to identify all EE objectives reported in the 42 papers found during the literature search. Then, EE objectives are grouped in high-level EE functions, according to the specific aims of each EE objective. At last, for all identified EE objectives, a set of remarks and guidelines, tools and relevant papers is suggested. It is expected that this alternative presentation of results facilitates the selection and implementation of relevant tools for EE related objectives in industry. Furthermore, the development of this framework enables a comprehensive overview of the reported EE objectives and a critical review of the field.

A total of 5 high-level EE functions were identified, each including a varying number of EE objectives. Results from Tables 7–13 also show that there are another two important high-level themes across the literature: (i) data pre-processing & transformation, and (ii) data correlation & selection. They do not classify as EE objectives or functions, but rather, play a very important

Table 10Key paper contents on *Energy Consumption Forecast*.

Reference	Tools and data workflows	EE insights
Liu et al. (2019)	<p>Transformation: Empirical mode decomposition (EMD) transforms historical series of energy consumption into a number of quasiperiodic intrinsic mode functions.</p> <p>Pre-processing: Moving Average Filter (MAF), smooths intrinsic mode functions, minimizing the effect of noise on data.</p> <p>Model: LSSVM and Quadratic Exponential Smoothing (QES) take intrinsic mode functions to predict future energy consumption.</p> <p>Validation: RMSE and MAPE used to check model accuracy.</p>	<ul style="list-style-type: none"> ● Approach utilized online during industrial operations. Processes a finite number of energy consumption points to forecast future energy consumption. ● Predictions for energy consumption are made for 1 to 4 steps ahead. As expected, the larger the number of steps ahead, the largest the prediction error.
Zhang et al. (2018a)	<p>Transformation I: Data normalization.</p> <p>Transformation II: Nonlinear function expansion from original set of input variables.</p> <p>Selection: PCA on original set of data and set of nonlinear variables from the transformation step to extract the most significant.</p> <p>Model: <i>Functional Link Neural Network</i> (FLNN) takes outputs from PCA as inputs to model energy consumption.</p> <p>Validation: RMSE for accuracy checks. Data split in training and test sets.</p>	<ul style="list-style-type: none"> ● This tool is an adaptation from the standard FLNN architecture. It uses PCA as a middle step to reduce the potential large number of inputs to the neural network. ● Two alternative ANN configurations proposed for comparison. ● Model obtained enables to estimate energy consumption as a function of process inputs.
Zhang et al. (2018b)	<p>Transformation: Data normalization.</p> <p>Selection: Input variables selected based on process insight.</p> <p>Model: Five parallel <i>ELM</i> neural networks, each using a different nonlinear function to transform process inputs. A weight from each network is determined using least squares, to map energy consumption to selected process inputs.</p> <p>Validation: Data split in training and test sets. Average Relative Error (ARE), Average Root Mean Squared Error (ARMSE) and Standard Deviation (SD) for testing prediction accuracy.</p>	<ul style="list-style-type: none"> ● Five standalone ELM neural networks used for prediction and all results compared. ● Energy consumption estimated indirectly via monitoring other process variables. ● Model obtained enables to estimate energy consumption as a function of process inputs.
Qin et al. (2018)	<p>Transformation: Collected data is categorized in two datasets, according to the nature of data.</p> <p>Selection: <i>Clustering</i> applied to multidimensional dataset to compress and obtain representative information from the original dataset.</p> <p>Model: <i>Merged Neural Network</i> used one of the original datasets as the first set of inputs, and the results from clustering as the second set of inputs to model energy consumption.</p> <p>Validation: RMSE and Model Correlation Coefficient (MCC) for accuracy checks. Comparison other ML algorithms.</p>	<ul style="list-style-type: none"> ● The number of clusters is customizable, and may be used as a parameter for fine tuning of performance. ● Approach is developed to predict energy consumption and obtain insights for operation of Additive Manufacturing machines.
Kovačič and Šarler (2014)	<p>Selection: Key units contributing to overall process energy consumption identified, and their consumptions over a period of 3 months collected.</p> <p>Model: <i>Genetic algorithm</i> (GA) applied, enabling total energy consumption forecast, and expressed explicitly as a function of key process inputs.</p>	<ul style="list-style-type: none"> ● Steel plant application. Strong focus on production plan, which may result in significant variations in electric energy demand for process operation. ● This tool is integrated with the production plan to adjust contracted power supply and enhancing economic performance and rational electric energy generation and distribution.

role in the development of methodologies for EE objectives. Given the importance of these subjects on data workflows within ML for insight extraction, they were also included in the proposed framework as *supporting tools*. Fig. 6 describes all high-level functions identified and their specific objectives.

Tables 14–20 provide details for all EE objectives identified in Fig. 6. Each table focuses on a single high-level EE function, and reports ML tools and other tools used to achieve the identified EE objectives, and relevant works from the literature search.

5.2. Critical review and research trends

Analysis and prediction EE functions seem to capture the most attention from the research community. They are vital for understanding the usually complex interactions between energy consumption and industrial plants. In this context, optimization is the most advanced EE function, as it requires in-depth understanding of the more basic functions. Optimization activities enable actual energy savings in industry, and thus it is expected that this function will receive a growing attention in future research.

Aside from EE functions, two issues that stand out from the proposed framework are: (i) noise and data uncertainty, and (ii) input variable selection. The first is vital to draw valid and useful results from the methodologies implemented. The second issue relates to what information should be selected for the development of EE methodologies. In large manufacturing and process

industries, the available information is often very extensive, and posing important challenges on what information to use. The strong focus of research on these activities is an indication that industry is only recently turning its attention to the potential of ML: these are among the first steps required in any data workflow using ML tools. Many more contributions across all identified categories are expected to enrich this field in a near future. In particular, there are several important concepts around Industry 4.0, such as Big Data and Internet of Things, which relate directly to Machine Learning and which will likely play an important role on future research.

As a final comment on results presented in Sections 4 and 5, it is worth noting that hundreds of papers beyond the set of 42 papers included in this framework were scanned, as schematically depicted in Fig. 4. Many of these include important contributions in the fields of EE, manufacturing and process industries or ML. These include, for instance, the works of Zou et al. (2019) using optimization for improved industrial EE, Geng et al. (2019a) using ML tools in an industrial setting for fault detection, or Han et al. (2020), where a more deterministic type of approach is used for industrial EE via the utilization of data. While there are in fact multiple additional publications dealing with these concepts, it must be stressed that only those papers articulating simultaneously these 3 key concepts were considered in this work.

Table 11
Key paper contents on *Energy Consumption Optimization*.

Reference	Tools and data workflows	EE insights
Shen et al. (2020)	<p>Model: Hybrid model of plant.</p> <p>Selection: <i>Support vector clustering</i> (SVC) applied to two process variables subject to uncertainty to capture the variability of the pair in the corresponding 2D space.</p> <p>Optimization: Energy consumption problem formulated as a MINLP and solved for a set of process flowrates while satisfying process steam and power demands.</p>	<ul style="list-style-type: none"> ● Deterministic and robust optimization problem formulations. ● Regularization parameter from SVC may be tuned to set how conservative is the robust optimization problem. ● Method targets energy saving and has important ties with the field of energy systems.
Qin et al. (2020)	<p>Transformation: Design dataset used to predict process dataset and build a second dataset, using <i>deep learning</i> techniques.</p> <p>Model: Design and process datasets used in second <i>deep learning ANN</i> model to predict energy consumption as a function of relevant process inputs and for distinct production objectives (modes).</p> <p>Validation: RMSE and MCC for accuracy checks.</p> <p>Optimization: PSO to optimize ANN energy consumption model.</p>	<ul style="list-style-type: none"> ● Methodology enables prediction, but focus mainly on process optimization. ● Restrictions on process operation carefully identified. ● Analysis of ANN parameters to identify most important process inputs. ● It provides a way to find a set of process inputs delivering the desired production objectives, while minimizing energy consumption.
Wang et al. (2018)	<p>Selection: Industrial data on consumption power partitioned according to a set of operating regimes.</p> <p>Model: <i>Multi-Layer Feed-Forward Neural Network</i> used on partitioned data for classification purposes.</p> <p>Validation: MAPE for accuracy checks.</p> <p>Monitoring: Power consumption profiles are monitored during online operation to identify key patterns useful for process management.</p> <p>Optimization: Optimization problem aiming at minimization of energy consumption is developed. The optimization problem is triggered during the monitoring stage when a set of conditions is observed.</p>	<ul style="list-style-type: none"> ● Methodology encompasses the concepts of Big Data, Cyber Physical Systems, Computer Numerically Controlled and Intelligent Immune Systems (I²S). ● This contribution is also related with fault detection, but with a great focus on energy optimization. ● The online monitoring procedure is framed around the concept of I²S, responsible for the management of the control strategy. ● The outcome of the optimization problem is a rescheduling of operations aiming at an improved performance. ● Warnings and scheduled maintenance tasks are also obtained as a result of this strategy.
Golka-rnarenji et al. (2018)	<p>Model: <i>Support vector regression</i> (SVR) used to predict key product property. First-principles/empirical modeling used to predict a second product property.</p> <p>Validation: MSE for accuracy checks. Data split in training and test sets.</p> <p>Optimization: <i>Genetic optimization algorithm</i> (GOA), defining energy consumption as the objective function and using the defined models and enforcing a set of constrains as minimal specifications for product quality.</p>	<ul style="list-style-type: none"> ● Two distinct optimization scenarios defined. ● Alternative tool based on the use of neural networks also proposed for comparison. ● Approach enables identification of inputs for optimal energy performance. Enables also to quantify the energy saving potentials.
Liang et al. (2018)	<p>Selection: Industrial data on consumption power partitioned according to a set of operating regimes.</p> <p>Model: ANN used on partitioned data for classification purposes.</p> <p>Validation: RMSE for accuracy checks.</p> <p>Monitoring: Power consumption profiles are monitored during online operation to identify key patterns useful for process management. Model encompasses the concept of an aging factor for equipment.</p> <p>Optimization: Optimization problem aiming at minimization of energy consumption is developed. The optimization problem is used in two instances: (i) optimal process scheduling, and (ii) rescheduling based on identified patterns.</p>	<ul style="list-style-type: none"> ● Methodology similar to the one proposed in Wang et al. (2018). ● Aging factor is identified as a differentiating factor. ● Scheduling and rescheduling activities for best utilization of energy and for general process performance.
Monedero et al. (2012)	<p>Pre-processing: Outliers identification and deletion from databank.</p> <p>Selection: Only points satisfying a technical pre-requisite are kept for modeling activities.</p> <p>Correlation: Chi square tests between pairs of variables to identify subset of most relevant variables for modeling.</p> <p>Model: <i>Discriminant Analysis</i> (DA) to capture EE in a detailed way as a function of relevant process variables.</p> <p>Validation: Data split in training and test sets.</p> <p>Optimization: Online search within stored databank of neighbor point for improving EE. ANN model included to provide additional optimization insight into operating domains not covered by recorded data.</p>	<ul style="list-style-type: none"> ● EE calculated as a ratio between plant energy consumption and material plant input. ● Strategy also takes into account which variables are controllable and which are not controllable, given control structure imposed on the system. ● Controls are set to the controllable variables of the identified neighbor point. ● Optimization focus on identifying historical points capable of improving current state. ● Interpolation tools based on the ANN framework are used to estimate further EE improvements beyond the known data.

6. Conclusions

In this paper, a review of contributions in the field on industrial Energy Efficiency using Machine Learning tools was presented. The first literature scans suggested that literature is significantly fragmented. This required a more elaborate literature review to ensure the majority of contributions in this field is captured in a systematic way. While it is unclear whether this was achieved in full, the utilization of cross references checks suggests that a very good picture of the current published works in the field was achieved, with a total of 42 papers found.

An analysis on the number of papers published per year shows that the number of publications has been increasing. This is most likely due to the emphasis put on rational energy utilization promoted recently by a number of agencies and governments

worldwide. It is also not surprising that this number is growing given the multiple capabilities ML tools offer for data processing and insight extraction, and the dawn of Industry 4.0 which is extensively promoting the use of such tools and supported on ever growing databases.

Petrochemicals, and namely ethylene production, dominates the attention of researchers with the vast majority of publications addressing the related energy challenges in this industry. China also dominates the contributions presented in this field and intimately related with the challenges on the Chinese petrochemicals industry. Only a small number of publications were found and addressing energy challenges in other industries, which is a clear indication that industry is only recently turning its attention to this topic.

Table 12Key paper contents on *Technology and Scale impact on EE*.

Reference	Tools and data workflows	EE insights
Han et al. (2017a)	Transformation I: Data normalization. Transformation II: FCM to obtain a set of clusters from plant data and from a number of units within the same sector (different technologies and scales). Model: Data fusion, based on all observations and defined clusters. Enables the calculation of weights for clusters and identifying an average or benchmark reference for a given set of technology and scale. Values calculated for various combinations of scale and technology.	<ul style="list-style-type: none"> ● Benchmarks obtained for different combinations of technology and scale. ● A set of graphs are produced to illustrate the impact of scale and production on the key process inputs and outputs. ● The approach does not allow for a formal EE indicator, but does provide useful information for technology and scale selection.
Strušnik et al. (2016)	Pre-processing: Outliers removal. Model: Adaptive Network-based Fuzzy Inference System (ANFIS) and first-principles model for computation of expected power consumption for two distinct technologies given a set of operating requirements.	<ul style="list-style-type: none"> ● Quantified power consumptions used as key factors for decision on most efficient technology.
Geng et al. (2012)	Pre-processing: Data consistency test using Grubbs test. Transformation: Daily data are fused into monthly and yearly data using Hierarchical Variable Variance Fusion (HVVF), yielding energy consumptions for the same technology. Model: Fuzzy Analytic Hierarchy Process (FAHP) and HVVF enable estimation of representative EE values per technology and scale.	<ul style="list-style-type: none"> ● EE is defined as a (relative) specific energy consumption. ● Scale and technology decisions based on EE.

Table 13Key paper contents on *EE Multi-objectives*.

Reference	Tools and data workflows	EE insights
Xu et al. (2020)	Transformation: Data normalization. Model I: ANN model and Intelligent Case Based Reasoning (ICBR) model used to estimate machine cutting power as a function of relevant model inputs and identifying distinct operation modes. Model II: Based on ANFIS architecture, to deliver three complementary models on cutting machine performance. Validation: MAPE, R^2 and RMSE for accuracy checks. Optimization: Multi-objective optimization to deliver the optimal process inputs for operation, using Vibration Particle Swarm Optimization (VPSO).	<ul style="list-style-type: none"> ● Features: energy consumption prediction and optimization. ● The ICBR framework is particularly adequate for the objectives proposed, as process operation includes distinct operation modes for different jobs. ● The first model predicts cutting power. ● The second model is optimized via VPSO to deliver optimal process settings for minimal energy consumption.
Zhu and Chen (2019b)	Selection: Partial Least Squares (PLS) to identify most significant input variables. Model: Gaussian Process (GP) to map input to output data. Prediction includes both an output estimate and associated uncertainty (estimated standard deviation). Additional samples added when uncertainty exceeds a predefined limit. Validation: RMSE for accuracy checks.	<ul style="list-style-type: none"> ● Features: EE estimation, production capacity forecast and energy optimization. ● Explicit definition of EE indicator, as a quotient between total products and total energy consumption. ● Ethylene yields predicted as a function of process inputs. ● Average efficiency level determined and used as benchmark for process operations. ● Criteria defined for unacceptable EE performance, triggering a set of corrective actions in the plant.
Zhu and Chen (2019a)	Selection: Neighboring database points to current process state are selected using Just In Time (JIT) learning / Least Squares Support Vector Regression (LSSVR). Pre-processing: Noise handling via QR decomposition. Model: State-space model identification relating inputs to outputs with Subspace Model Identification (SMI). Validation: Average accuracy for accuracy checks.	<ul style="list-style-type: none"> ● This contribution deals with EE estimation and production capacity forecast. ● EE calculations based on explicit indicator using input energy consumption and production output. ● Online data measurement, and continuous update of state-space model with the aim to forecast production accurately.
Gong et al. (2019)	Benchmark: EE metric for total production and ethylene production using input–output data. DEA may be used to identify benchmarks. Transformation: Data normalization. Model: FLANN used to map input–output data. Validation: Data split in training and test sets. RMSE and Mean Average Error (MAE) for accuracy checks. Optimization: Optimization problem formulated to minimize the distance to the EE benchmark metric and subject to the FLANN model developed. Set of constraints imposed to reflect technical specifications. PSO is the optimization engine.	<ul style="list-style-type: none"> ● Features: energy consumption optimization and EE analysis. ● Optimization enables optimal operation from an EE point of view. ● A set of plots are generated and allowing additional EE insights.
Meng et al. (2018)	Model I: RBFNN model of cracking furnace, including a total of 7 inputs and 8 outputs. Validation: Data split in training and test sets. ARE for accuracy checks. Selection: Four EE indicators developed based on engineering insight using available process variables. Baselines: Calculation of dynamic baselines (worst and optimal performance) for EE indicators using Sequential Quadratic Programming (SQP) and subject to developed ANN model. Model II: Calculation of global EE indicator, by assignment of weights to individual indicators using AHP or Correlation Coefficient (CC).	<ul style="list-style-type: none"> ● Features: predictive capabilities for plant performance, and a useful framework for analysis and optimization. ● It is one of the most elaborate contributions articulating several tools and objectives. ● One of the key focus is assessment of the impact of production load on EE and obtaining meaningful baselines for EE calculation. ● RBFNN model enables prediction of all output variables of interest. ● Baselines are used for EE analysis and optimization opportunities. ● A tailored EE index is suggested. ● DEA models used for comparison.

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Table 13 (continued).

Reference	Tools and data workflows	EE insights
Zhu and Chen (2018)	<p>Transformation: Data normalization.</p> <p>Correlation: <i>Ordinary Least Squares</i> (OLS) to estimate energy consumption associated with each manufactured product.</p> <p>Selection/Model: PCA used to select only most significant energy streams, hence resulting in a simplified production model.</p> <p>Model: Efficiency index calculated based on developed models.</p>	<ul style="list-style-type: none"> ● Features: prediction, analysis and optimization. ● EE analysis by comparing present EE indicator against benchmark. ● When efficiency index falls below a defined threshold, it triggers corrective actions for fault inspections, and additional data mining activities to promote energy optimization. ● Utilization of OLS/PCA approach to deal with noise and redundant data.
Velázquez et al. (2013)	<p>Pre-processing: Outliers deletion, selection of variables within specified range.</p> <p>Transformation: Categorization of continuous variables into classes (e.g. “very high”, ..., “very low”). Data normalization.</p> <p>Selection/Model: Selection of key influence variables via <i>Discriminant Function Analysis</i> (DFA) for specific consumption model.</p> <p>Validation: Data split in training and test sets. R^2 for accuracy checks.</p>	<ul style="list-style-type: none"> ● Features: estimation, analysis and optimization. ● EE indicators derived for three plant sections and expressed as specific energy consumptions. ● Enables the calculation of three energy related indicators, using baseline and target reference, as well as actual consumptions: (i) achieved savings, (ii) potential savings and (iii) efficiency ratio. ● Model results enable identification of key variables for performance and provides valuable information for plant optimization.
Lau et al. (2008)	<p>Transformation: Data fuzzyfication.</p> <p>Model: <i>Fuzzy inference engine</i> (FIE), maps key process inputs to process energy consumption change.</p> <p>Transformation: Defuzzyfication to obtain predictions for (crisp) energy consumption change.</p>	<ul style="list-style-type: none"> ● Features: forecast energy consumption and guidelines for optimization. ● Prediction of energy consumption trend in the context of clothing industry where activity levels undergo regular fluctuations. ● Application enables switching off idle machines, adjusting production plan, and providing key information to review contracted power.

Table 14Objectives and remarks relating to *EE Estimation*.

Objective	Remarks and guidelines
Energy efficiency metrics resolution	<ul style="list-style-type: none"> ● Common issue for all DEA based tools, where typically a large number of units are close to 100% efficiency. ● Tools are required to provide more resolution into efficiency metrics and allow managers to identify more clearly the most efficient units, process configurations or input specifications. ● ML tools: AP. ● Other tools: DEACM. ● Relevant contributions: Geng et al. (2019b) and Han et al. (2019b).
Benchmark & Baseline identification	<ul style="list-style-type: none"> ● Benchmarks are often used to provide context for EE calculations. ● This includes identification of baselines, best performing units for purposes of EE assessment and often relying on comparisons between two or more reference points. ● ML tools: Fuzzy logic, FCM. ● Other tools: BDP, DEA, DEACM, FAHP, HVVF, SQP. ● Relevant contributions: Geng et al. (2019b), Han et al. (2019b), Beisheim et al. (2019), Zhu et al. (2018), Geng et al. (2018a), Gong et al. (2017b), Han et al. (2015), Geng et al. (2020), Han et al. (2019c,a), Geng et al. (2018c), He et al. (2018), Geng et al. (2018b), Han et al. (2018), Geng et al. (2017b,c), Han et al. (2017b), Geng et al. (2017a), Gong et al. (2017a), Han et al. (2016, 2017a), Geng et al. (2012), Zhu and Chen (2019b), Gong et al. (2019), Meng et al. (2018), Zhu and Chen (2018) and Velázquez et al. (2013).

EE Functions:

<p>Estimation</p> <ul style="list-style-type: none"> ● Energy efficiency metrics resolution ● Benchmark and baseline identification 	<p>Analysis</p> <ul style="list-style-type: none"> ● Operating modes classification and identification ● Identification of saving potentials and energy savings ● Identification of key variables for energy efficiency ● Quantification of energy consumption per product 	<p>Optimization</p> <ul style="list-style-type: none"> ● Corrective actions ● Optimal scheduling ● Optimal control ● Optimal process settings ● Robustness
<p>Prediction</p> <ul style="list-style-type: none"> ● Input-output model development ● Energy consumption trend prediction 		<p>Technology & scale</p> <ul style="list-style-type: none"> ● Technology assessment ● Scale assessment

Supporting tools:

<p>Data pre-processing & transformation</p> <ul style="list-style-type: none"> ● Noise and data uncertainty ● Data consistency 	<p>Data correlation & selection</p> <ul style="list-style-type: none"> ● Input variable selection ● Limited available data (low fidelity) ● Data compression
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Fig. 6. Framework for industrial EE related goals using ML tools.

The papers found in this literature search were analyzed for their technical content and results summarized in a series of tables. The contributions in the field of industrial EE via ML tools is fully captured in these tables. This includes both information on

ML and other tools used in each contribution, as well as specific information on how these methodologies are used to extract valuable EE insights.

Table 15Objectives and remarks relating to *EE Analysis*.

Objective	Remarks and guidelines
Operating modes classification and identification	<ul style="list-style-type: none"> ● This topic less frequent for steady-state type processes, but frequent on industries where different stages are implicitly identified. ● Identifying these stages or process modes provide key insights for process analysis and supporting corrective/optimization actions. ● ML tools: ANN, k-means. ● Other tools: BDP, ICBR. ● Relevant contributions: Beisheim et al. (2019), Gong et al. (2017b), Qin et al. (2020), Wang et al. (2018), Liang et al. (2018) and Xu et al. (2020).
Identifying saving potentials and energy savings	<ul style="list-style-type: none"> ● Saving potentials quantify the present excess of energy consumption, therefore providing a driving force for improvement. ● Energy savings analysis compares current energy consumption with projected scenario before EE action put in place. ● ML tools: ANN, Fuzzy logic. ● Other tools: DEA, DEACM, GOA, ISM, results/graph analysis. ● Relevant contributions: Geng et al. (2019b), Han et al. (2019b), Beisheim et al. (2019), Zhu et al. (2018), Geng et al. (2018a), Gong et al. (2017b), Han et al. (2015), Geng et al. (2017b), Han et al. (2015), Geng et al. (2020), Han et al. (2019c,a), Geng et al. (2018c,b), Han et al. (2018), Geng et al. (2017b), Han et al. (2017b), Geng et al. (2017a), Gong et al. (2017a), Han et al. (2016), Golkarnarenji et al. (2018), Liang et al. (2018), Gong et al. (2019), Meng et al. (2018) and Velázquez et al. (2013).
Identify key variables for energy efficiency	<ul style="list-style-type: none"> ● Relates to the variable selection problem identified in Table 20. ● When possible, it is desirable to find a restricted group of variables with the highest impact on EE. ● ML tools: ANN, DFA, GP. ● Other tools: BE, DEA, ISM, results/graph analysis. ● Relevant contributions: Beisheim et al. (2019), Zhu et al. (2018), Geng et al. (2018a), Gong et al. (2017b), Han et al. (2015), Geng et al. (2020), Han et al. (2019a), Geng et al. (2018c,b), Han et al. (2018), Geng et al. (2017c), Han et al. (2017b), Geng et al. (2017a), Gong et al. (2017a), Han et al. (2016), Qin et al. (2020), Xu et al. (2020), Zhu and Chen (2019b), Meng et al. (2018) and Velázquez et al. (2013).
Quantify energy consumption per product	<ul style="list-style-type: none"> ● Large industrial processes include many energy sources and produce a variety of products. ● Estimating energy spent on each product is not a trivial problem, though a very useful piece of information. ● ML tools: OLS. ● Relevant contributions: Gong et al. (2019) and Zhu and Chen (2018).

Table 16Objectives and remarks relating to *EE Prediction*.

Objective	Remarks and guidelines
Input–output model development	<ul style="list-style-type: none"> ● Most common theme across all identified papers. ● Prediction may focus on a variety of objectives, including production, energy consumption and EE prediction. ● ML tools: ALAMO, ANN (multiple ANN architectures), DA, DFA, FCM, FIS, GA, GP, LSSVR, SVR. ● Other tools: AHP, CC, CF, DEA, First-principles modeling, IDA, JIT, Hybrid modeling, SMI. ● Relevant contributions: Beisheim et al. (2019), Zhu et al. (2018), Geng et al. (2020), Han et al. (2019c,a), Geng et al. (2018c), He et al. (2018), Geng et al. (2018b), Han et al. (2018), Geng et al. (2017b,c), Han et al. (2017b), Geng et al. (2017a), Gong et al. (2017a), Han et al. (2016), Zhang et al. (2018a,b), Qin et al. (2018), Kovačič and Šarler (2014), Shen et al. (2020), Qin et al. (2020), Golkarnarenji et al. (2018), Monedero et al. (2012), Strušnik et al. (2016), Xu et al. (2020), Zhu and Chen (2019b,a), Gong et al. (2019), Meng et al. (2018) and Velázquez et al. (2013).
Energy consumption trend prediction	<ul style="list-style-type: none"> ● Focus on past energy consumptions to forecast energy consumption trend. ● Relates with supply and demand for adequate EM. ● ML tools: FIE, LSSVM. ● Other tools: EMD, QES. ● Relevant contributions: Liu et al. (2019) and Lau et al. (2008).

Table 17Objectives and remarks relating to *EE Optimization*.

Objective	Remarks and guidelines
Corrective actions	<ul style="list-style-type: none"> ● Corrective actions to be implemented as a result of some optimization activity to improve EE. This includes fault detection checking or raising warnings for undertaking general system troubleshoot. ● Custom made tools reported. ● Relevant contributions: Zhu and Chen (2019b, 2018) and Lau et al. (2008).
Optimal scheduling	<ul style="list-style-type: none"> ● Particularly useful to industries operating on varying production plans. ● Tools allow for optimal selection of scheduling and idle machines switching off for enhanced energy performance. ● Tools: I²S. ● Relevant contributions: Wang et al. (2018) and Liang et al. (2018).
Optimal control	<ul style="list-style-type: none"> ● Set of tools based on formal optimization tools or database assessment for finding optimal process inputs minimizing energy consumption. ● ML tools: ANN, GOA. ● Other tools: MINLP, PSO. ● Relevant contributions: Shen et al. (2020), Golkarnarenji et al. (2018), Monedero et al. (2012), Gong et al. (2019) and Velázquez et al. (2013).

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Table 17 (continued).

Objective	Remarks and guidelines
Optimal process settings	<ul style="list-style-type: none"> ● Applies mostly to batch type processes and with focus on finding the best process inputs for a specific production objective and improving EE. ● Tools: PSO, VPSO. ● Relevant contributions: Qin et al. (2020) and Xu et al. (2020)
Robustness	<ul style="list-style-type: none"> ● Address the challenges associated with uncertainty or disruptive events in optimization, to ensure feasible optimization solutions. ● ML tools: SVC ● Relevant contributions: Shen et al. (2020)

Table 18Objectives and remarks relating to *EE Technology*.

Objective	Remarks and guidelines
Technology assessment	<ul style="list-style-type: none"> ● Tools process historical and lab scale data to obtain insight on most EE technologies. ● ML tools: ANN, FCM. ● Other tools: FAHP, HVVF, results/graph analysis. ● Relevant contributions: Geng et al. (2018b), Han et al. (2017a), Strušnik et al. (2016) and Geng et al. (2012).
Scale assessment	<ul style="list-style-type: none"> ● Drawing insight into this subject promotes efficient design, and plant management, via scheduling, for improved performance. ● ML tools: ANN, FCM. ● Other tools: FAHP, HVVF, results/graph analysis. ● Relevant contributions: Geng et al. (2018b), Han et al. (2017a) and Geng et al. (2012).

Table 19Objectives and remarks relating to *Data pre-processing & transformation*.

Objective	Remarks and guidelines
Noise and data uncertainty	<ul style="list-style-type: none"> ● Noise affects reliability of results and the confidence of decisions taken. Relates to data measurement and pre-processing. ● ML tools: Fuzzy logic, OLS, PCA, SVC. ● Other tools: MAF, QR decomposition. ● Relevant contributions: Zhu et al. (2018), Geng et al. (2018a), Han et al. (2015, 2018), Geng et al. (2017b), Liu et al. (2019), Shen et al. (2020), Geng et al. (2012), Zhu and Chen (2019b,a, 2018) and Lau et al. (2008).
Data consistency	<ul style="list-style-type: none"> ● Some processes may experience dynamic/delay effects, where others may include a huge number of measurements, and possibly subject to systematic bias, or data acquisition errors. ● Consistent data is key for model development and model accuracy. ● Tools: Data checks (e.g. mass balances), Grubbs test. ● Relevant contributions: Beisheim et al. (2019), Gong et al. (2017b), Han et al. (2015, 2018, 2017b, 2016), Monedero et al. (2012), Strušnik et al. (2016), Geng et al. (2012) and Velázquez et al. (2013).

Table 20Objectives and remarks relating to *Data correlation & selection*.

Objective	Remarks and guidelines
Input variable selection	<ul style="list-style-type: none"> ● One of the key difficulties reported across the majority of contributions, especially in the context of large scale industries. ● It is highly desirable to identify the minimum set of variables with relevance for the EE objectives defined. ● Removing redundancy, facilitating analysis and attaining computationally and time efficient tools is a key motivation for this. ● Two important trends identified: the first, focuses on manual variable selection based on experience, and the second on using a wide range of mathematical tools. ● ML tools: AP, PCA, PCR, PLS. ● Other tools: AHP, based on experience, ISM. ● Relevant contributions: Geng et al. (2019b), Han et al. (2019b), Zhu et al. (2018), Gong et al. (2017b), Geng et al. (2018c,b, 2017b), Han et al. (2017b), Geng et al. (2017a), Zhang et al. (2018a,b), Zhu and Chen (2019b), Meng et al. (2018) and Zhu and Chen (2018).
Limited available data (low fidelity)	<ul style="list-style-type: none"> ● Data available may be insufficient to obtain desired fidelity. ● In this case, tools are required to extract the most value from available data. ● ML tools: NIVSG. ● Other tools: MC, PSO. ● Relevant contributions: He et al. (2018) and Gong et al. (2017a).
Data compression	<ul style="list-style-type: none"> ● Transformation of a large set of data points in a smaller and representative set of points. ● Large datasets can often be represented using much smaller datasets which include important information and enable much faster computations. ● ML tools: AP, FCM, k-means. ● Relevant contributions: Beisheim et al. (2019), Han et al. (2019c), Geng et al. (2017b) and Qin et al. (2018).

At last, a framework for the utilization of ML tools on industrial EE problems was suggested, where a number of high-level

themes and specific EE objectives are identified. This serves as a snapshot of the present development of this field and also offers

guidance for industry on selection of relevant ML and other useful tools to address energy related challenges.

Declaration of competing interest

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

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