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Review

Overview of Natural Gas Boiler Optimization Technologies and Potential Applications on Gas Load Balancing Services

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Abstract: Natural gas is a fossil fuel that has been widely used for various purposes, including residential and industrial applications. The combustion of natural gas, despite being more environmentally friendly than other fossil fuels such as petroleum, yields significant amounts of greenhouse gas emissions. Therefore, the optimization of natural gas consumption is a vital process in order to ensure that emission targets are met worldwide. Regarding residential consumption, advancements in terms of boiler technology, such as the usage of condensing boilers, have played a significant role in moving towards this direction. On top of that, the emergence of technologies such as smart homes, Internet of Things, and artificial intelligence provides opportunities for the development of automated optimization solutions, which can utilize data acquired from the boiler and various sensors in real-time, implement consumption forecasting methodologies, and accordingly provide control instructions in order to ensure optimal boiler functionality. Apart from energy consumption minimization, manual and automated optimization solutions can be utilized for balancing purposes, including natural gas demand response, which has not been sufficiently covered in the existing literature, despite its potential for the gas balancing market. Despite the existence of few research works and solutions regarding pure gas DR, the concept of an integrated demand response has been more widely researched, with the existing literature displaying promising results from the co-optimization of natural gas along with other energy sources, such as electricity and heat.

Keywords: domestic gas boiler; energy efficiency; consumption minimization; demand response; gas balancing; integrated demand response

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Citation: Tsoumalis, G.I.; Bampos, Z.N.; Chatzis, G.V.; Biskas, P.N. Overview of Natural Gas Boiler Optimization Technologies and Potential Applications on Gas Load Balancing Services. *Energies* **2022**, *15*, 8461. https://doi.org/10.3390/en15228461

Academic Editors: Yukun Hu, Mirko Morini, Dionysia (Denia) Kolokotsa, Erik Dahlquist and Esko Juuso

Received: 9 October 2022
Accepted: 9 November 2022
Published: 12 November 2022

1. Introduction

Climate change as a result of global warming is gradually becoming an important issue of modern society. Its main cause is greenhouse gas emissions, which constitute the result of mainly anthropogenic activities involving the burning of fossil fuels, which currently supply more than 85% of the worldwide energy consumption, and their use is constantly increasing [1], despite the fact that they are finite resources [2]. Such applications include energy generation and energy related activities in domestic and tertiary buildings. Another important problem that our society is facing is energy poverty, which currently remains a problem even for developed countries and is strongly linked to modern living standards, affecting the health and the emotional state of those facing it [3]. In order to address these issues, multiple options are examined towards the sustainability and accessibility of energy, including (a) the transition to clean renewable energy sources such as solar, wind, and hydroelectric energy [4], (b) the switch to more environmentally friendly fuels, such as shale gas and natural gas [5,6], even as transitory fuels towards full decarbonization by the year 2050 [7], and (c) the efficiency improvement of existing energy consumption units [8,9] such as industrial, commercial, residential, and public buildings. For the latter, in the European Green Deal, there are provisions that require Member States to renovate at least 3% of the total floor area of all public buildings annually and a multitude of other provisions for energy efficiency actions [10].

The emerging technologies of smart grids, artificial intelligence, Internet of Things, and smart homes provide the base of new solutions that can also lead to this direction. The aforementioned technologies provide a great opportunity to develop natural gas energy efficiency solutions, utilizing data from buildings in real-time and deploying control methodologies accordingly. The control methodologies developed for optimizing energy efficiency can also be used as the base for systems targeted at scheduling and shifting energy loads throughout the day, while taking into consideration user comfort. These solutions concern demand response (DR), which is the concept of increasing or decreasing an energy load in order for the supply to match the demand and, therefore, to help keep the grid stable. DR has been mainly implemented in electric loads during the last years, both in terms of research and of practical applications [11]. However, during the last years, the same concept was assessed for other energy carriers, including natural gas, and even for the combination of multiple energy sources, which defines integrated demand response [12].

The main purpose of the current work was to outline and review the existing methodologies regarding natural gas boiler optimization, including both manual and automatic techniques. Based on the methodologies described, we discuss (a) whether the above techniques can be used to provide balancing services in the natural gas markets in a similar way to which electricity load control methodologies are used to provide DR in the power system, (b) what other solutions exist in this topic, and (c) what other research topics could be helpful in the above process (e.g., gas load forecasting techniques as part of the control process). Finally, this work reviews how natural gas DR can be used along with other energy sources optimizations, shaping integrated DR (IDR) solutions, and provides insights on what methodologies are covered and which future research directions are expected to follow.

Initially, Section 2 provides the energy efficiency initiatives in the European Union. In Sections 3 and 4, the paper focuses on domestic buildings/environments that use natural gas in order to cover their heating needs, and it reviews existing technologies/methodologies used for the minimization of natural gas consumption, commenting on the expected environmental and financial impact of such solutions. In Section 5, the characteristics of the natural gas market are outlined, and various gas system scheduling and balancing approaches are presented, some of which deploy similar methodologies to the solutions mentioned in the previous section. Since natural gas is also used in electricity generation, the development of optimization methods aimed at the simultaneous scheduling and balancing of electricity and gas systems are assessed in Section 6, where the concept of integrated demand response in multi-energy systems is also presented and reviewed. Finally, Section 7 presents the conclusions drawn, summarizing the critical issues that have been already solved and the main challenges that remain unresolved, and it provides useful insights to where the current research and development is heading.

2. Energy Efficiency Initiatives

Over the years, the evolution of the technical and commercial viability of new technologies such as IoT and artificial intelligence has created new opportunities to develop and deliver energy efficiency-oriented solutions. Indeed, multiple mid- and long-term plans have been established to drive towards a greener future, such as the European Union 2030 Climate and Energy Framework, which, among other key objectives, defined the targets of decreasing greenhouse gas (GHG) emissions by at least 40% and improving the overall EU energy efficiency by at least 32.5% until 2030 [13]. The EU also proposed a set of long-term targets, aiming to become completely climate-neutral by 2050 [14]. Based on the above, the EU updated its energy policy framework and published eight new energy rules aiming to make an impact in terms of the consumer perspective, the environment, and the economy [9]. These rules, most of which are defined by legislative initiatives, must be adopted by all EU countries and converted into national law, and they include directives towards building energy performance improvement and an energy efficiency increase [15].

The European Commission, through funding programs such as "Horizon 2020" and "Horizon Europe", offers incentives to researchers to develop innovative solutions towards energy efficiency. Such an example is the "Secure, Clean and Efficient Energy" section of the "Horizon 2020" program, in which about six billion euros were invested for non-nuclear energy research purposes for the period 2014–2020, with the main priority being the energy efficiency sector [16]. In response to the energy efficiency targets set by the EU, the member states also implemented various measures to promote actions towards energy efficiency. For instance, Germany, which is one of the most energy efficient countries in the world at the moment, implemented a variety of policies and measures targeted both at residential and industrial buildings [17]. Regarding residential buildings, there are two energy efficiency incentives: (a) federal funding for the improvement of the efficiency of existing buildings and (b) tax reductions for the application of energy-related solutions.

Another, more global, approach was defined by the Paris Agreement [7], which was initiated in 2015, when it had effect on 55 countries, accounting for 55% of total global greenhouse gas emissions. More countries are continuously joining the agreement, accounting for a total of 189 parties that ratified until May 2020 [18]. Its main purpose is to limit the increase of the global average temperature to 1.5 °C compared to pre-industrial levels and to help developing countries make a transition to newer energy efficiency-oriented technologies.

In a similar fashion, the Clean Energy Ministerial was formed in 2010, which constitutes a global forum where major economies cooperate in order to share and promote the best practices and policies towards a global clean energy economy. Major global economies are represented among the participant countries, including China, which has also made commitments to minimize its carbon footprint by reducing their carbon dioxide emissions by 60–65% compared to 2005 levels by 2030.

All the described initiatives define objectives that align with the development of energy efficiency-oriented solutions. In this paper, several solutions regarding the optimization of natural gas consumption in domestic buildings are assessed with respect to the aforementioned objectives. In addition, the development of large-scale natural gas balancing services is also evaluated in the following sections, since such services could (a) alter the current gas market structure, creating increased competition in the gas balancing market, and (b) lead towards an intelligent demand response (DR) approach where both the financial and environmental aspect can be taken into account in the form of an adaptive multi-objective optimization problem, similar to electricity DR [11].

3. Domestic Heating

Domestic heating is as necessary today as it has been for the entire human history so far, and its need is steadily increasing due to the respective increase of the world population. While for the largest part of the last century the fuel used to generate heat was oil or some of its byproducts, in the current century, other fuels and heating systems are gaining popularity [19], and amongst them is natural gas. Natural gas is a naturally born, non-renewable hydrocarbon gas mixture with multiple uses, including cooking, heating, mobility (in the form of compressed natural gas or CNG), and electricity generation in open-cycle and combined-cycle gas turbines (OCGTs and CCGTs, respectively).

The reason for its extended use (natural gas dominates the European heating and energy supply [20]) is the fact that it offers a superior conversion efficiency compared to other fuels (coal, crude, oil products, etc.). It also emits considerably lower amounts of carbon dioxide when burned. This last feature aligns perfectly with the global initiative to reduce global warming, making natural gas the ideal fuel, both efficient and more environmentally friendly than other alternatives. This is the reason why natural gas has been designated by the European Commission as a transitory fuel towards the envisioned full decarbonization target in the year 2050.

The technology of the boiler plays an important role in both the composition and amount of greenhouse gases emitted when gas is burned, but the key feature for any type of user, residential or industrial, is energy efficiency. Older technology boilers, also known as conventional boilers, are less efficient and environmentally friendly compared to condensing boilers. Condensing boilers consume less fuel and have a 23% lower environmental impact [21]. It is worth noting though that, according to a national study carried out in Italy, the national consumption for domestic heating has not increased substantially, and the average NO_x emissions decreased thanks to advancements in boiler technology, despite the increase in demand for natural gas during the period 1999–2011 [22]. An extensive analysis of boiler technology is provided in Section 4.

In order for the fuel to reach the boiler, the house must be initially connected to the gas distribution network, analogously to the electrical grid. The gas enters the pipelines in the injection points (gas wells and/or storage facilities), and it flows through the transportation and distribution networks in order to reach the consumers' houses to be deployed. This is the traditional approach, where combustion takes place locally to serve the needs of an individual house. In some cases, the expansion of modern-day cities and the rising number of buildings connected to the gas network call for a new, more centralized approach. A general model designed to achieve the coordinated development of centralized supply systems fueled by natural gas is opted for in some cities, by combusting gas in heating plants outside or nearby each city and distributing the heat energy through a district-heating system to the end-consumers within the city [23].

Considering all the characteristics of natural gas mentioned above, both (a) for the user's economic benefit through the abundance of available customized solutions and (b) for reduced environmental impact, it becomes clear that natural gas will keep playing a major role in domestic heating in the foreseeable future.

4. Efficiency Optimization

Achieving higher energy efficiency and lower greenhouse gas emissions is a never-ending process leading to modifications in boilers and more efficient, environmentally friendly solutions. In this section, some well-known evolutions and breakthrough solutions are presented, categorized as follows:

- technological advancements in the construction phase;
- boiler operation manual improvement techniques;
- automated optimization during the boiler operational phase.

Each one of the above solutions contribute to the improvement of domestic boiler performance. The hereinafter described solutions belong to three main categories in chronological order, as summarized in Figure 1.

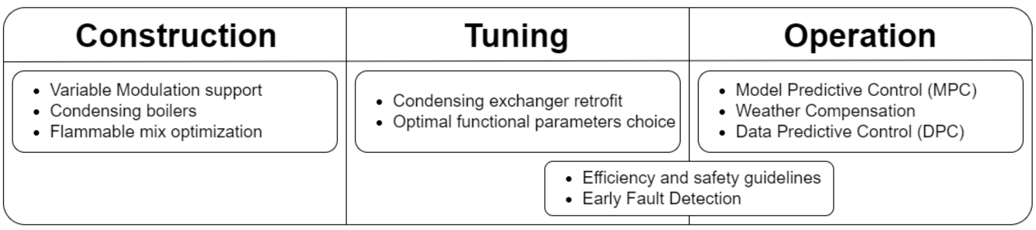

Figure 1. Boiler efficiency optimization techniques in each phase.

4.1. Boiler Technological Advancements in the Construction Phase

Boiler systems have been widely utilized for a long time as the driving force behind the industrial revolution, but initially they were not introduced in domestic environments until the middle of the 20th century in the form that are used today [24]. Traditional boilers were designed with only one mode of operation, i.e., on-off. This means that they could operate only at their full rated capacity. Thus, in many cases, the boiler would turn on, in order to satisfy the load, and then turn off again, multiple times, increasing the number of boiler cycles. This increase in boiler cycles leads to cycle losses, which makes the boiler less energy efficient and adds to the wear of the equipment. An important innovation that reduced the amount of boiler cycles is the boiler's ability to modulate its output in a continuous manner, namely, to operate within a range between the minimum and the maximum modulation level [25]. Manufacturers started offering units with multiple firing rates, which allow the system to adapt its response according to the load and not operate in full mode. As a result, most modern boilers are modulated.

Another major upgrade for domestic heating was the introduction of condensing boilers. In a traditional, non-condensing boiler, some heat is wasted in the form of hot gases released from the flue, whereas condensing boilers capture that heat and transfer it to water returning from the central heating system. This process results in a lower temperature of combustion products, recycling of the exhaust gas through the condensing heat exchanger, and reduced CO_2 emissions. All these characteristics make condensing boilers safer and more environmentally friendly, with the added benefit of being more efficient, reaching an efficiency level up to 99%. This high efficiency level is achieved by using waste heat in flue gas to preheat the cold water entering the boiler [26]. Inquiries have also been made in the direction of materials used for various components of the boiler. In a paper written by Liu et al. on emissions and thermal efficiency in premixed condensing gas boilers, two different types of burners were examined, metal fiber and stainless steel, in different heat loads and air rates to define which is most suitable and efficient for condensing boilers [27].

Other attempts to reduce the environmental impact, whilst achieving satisfactory combustion performance, include the use of different combustion catalysts [28]. Several European manufacturers offer domestic gas boilers that are able to burn gases of different compositions with the automatic adjustment of the excess air ratio. One of the cases examined is a mix of natural gas and hydrogen. Xin et al. performed simulations to determine the best hydrogen to natural gas volume ratio during combustion and concluded that the hydrogen mixing technique can help increase the combustion temperature and rate and reduce flue gas and CO2/NOx emissions [29]. The presence of hydrogen, which is highly flammable, requires increased control over the combustion process; the types of systems used to control the combustion process in natural gas fired residential boilers are "Flue gas analysis" and "Flame ionization" [30].

4.2. Boiler Operation Manual Improvement Techniques

Manual optimization is used to describe any process that can improve a boiler's functionality from the design and production phase to the installation and commencement of operation. From the first day of their conception, boilers are designed and built with the target of maximum efficiency. Nowadays, there are guidelines and practices manufacturers can deploy when designing a boiler regarding their efficiency and safety [31,32]. These practices are crucial in ensuring that the boiler operates in its optimal state; neglecting them can cause significant performance issues.

However, there is still room for improvement. As mentioned above, natural gas boilers are divided into two categories depending on whether they recapture escaping heat from flue gases: conventional and condensing. It is worth noting that a conventional boiler can be retrofitted to a condensing one even after its installation [33]. This results in the significant improvement of the efficiency of the boiler by a simple addition of a condensing heat exchanger, and it can be applied after the construction phase.

Another important procedure that is commonly overlooked and plays a crucial role in a boiler's operation, wear, and life expectancy is maintenance. Many users neglect the fact that their boiler is a machine that requires regular tuning to perform nominally. The importance of maintenance is such that research has been devoted to finding models to predict the required maintenance on buildings considering user discomfort [34]. Additionally, frequent maintenance increases the systems reliability, reduces boiler hazards, and potentially keeps down costs [35], while at the same time mitigating any potential health risks to the residents of the building [36]. Automatic early fault detection can help the process of proper maintenance by alerting the residents when a possible operational issue is detected. Achieving sufficient accuracy in the fault detection process is significant in this context. Shohet et al. tested a variety of machine learning algorithms (K-nearest neighbor, decision tree, random forest, and support vector machine) in a simulated environment with 14 different boilers [37]. The results were impressive, displaying an accuracy of over 95% in the models trained for each boiler, but generalization was not possible. This indicates that, with the described methodology, it is difficult to create a single robust model that can be used as a generalized approach for fault detection in all boilers, but, instead, models can be trained for each boiler specifically, deployed during the tuning phase, and installed before the operational phase to inform the user of possible faults, which would then require manual fault fixes to be applied.

Finally, the functional parameters of the boiler's operation can play a crucial role in its efficiency during its normal daily operation. Wu et al. [38] optimized the boiler's efficiency by employing an artificial bee colony (ABC) algorithm in order to determine the functional parameters (exhaust gas temperature, volume percentage of O_2, combustible material in fly ash, and boiler load percentage) that minimize the system's heat losses, based on the model of boiler combustion efficiency. The resulting parameters can be used to fine-tune the boiler before its operational phase and after its construction to ensure optimal efficiency. The test case displays that the ABC methodology performs better than a genetic algorithm (GA), achieving quicker convergence and increased robustness.

Nevertheless, despite the fact that the literature is mainly focused on the optimization of individual boilers' efficiency, the authors of [39] introduced an interesting conclusion about the zonal controlling of domestic heating, where zonal controlling means heating the rooms of the residence only when they were 'occupied'. In a pilot study of an 8-week winter test period in the UK, a house with zonal control used 11.8% less gas, despite a 2.4 percentage point drop in average daily boiler efficiency, compared to conventionally controlled heating. This minor parametrization technique indicates the significance of the added value that a smart heat system could have and the huge potential of automated solutions.

4.3. Automated Optimization during the Boiler Operational Phase

As discussed above, achieving higher efficiency levels of energy usage, particularly for natural gas boilers that constitute the main subject of this work, and minimizing greenhouse gas emissions constitute primary objectives of the EU Energy policy [13]. The methods discussed in the previous sections mainly focus on well-known practices, improvements during the design phase, or the addition/upgrade of various compartments that can boost a boiler's performance. However, the rapid growth of data science and the development of smarter algorithms has opened new opportunities that allow for further improvements in machine operations through the analysis and application of software tools. These new capabilities can help us tune the machines to operate optimally, but they also provide the added value of offering real-time automated solutions that require minimal outside/human intervention.

In order to create energy efficient buildings and deploy solutions regarding automatic control, one must firstly gain a better understanding of the various factors affecting their energy consumption and efficiency performance. The first step to this process is the development of an evaluation model that performs effectively for multiple types of buildings. Such a model was implemented, using multi-scale analysis, and tested by Tronchin et al. [40]. Among the various parameters used for such a system, a crucial parameter is the building's energy rating, since it holds significant information regarding its thermal behavior. Aiming for a specific building energy profile and being able to account for it during its design phase can prove to be a significant advantage [41], with the derived data being potentially helpful in the selection and tuning of both manual and automated efficiency optimization solutions deployed later on.

A boiler is designed and built in an environment that has quite different conditions from the one it is called to operate in. This fundamental difference calls for additional actions to ensure that every boiler performs optimally depending on the environment it is placed and installed in. Weather is an important aspect when attempting to provide heating for a building/home. It is constantly changing and can be quite unpredictable. Thus, any system responsible for heating should be quick to adapt to weather changes and be able to predict, to a certain degree, its future behavior. Weather compensation is the ability of a system to account for the weather variations and tune itself to operate in the most efficient way, providing a remarkable base for automated optimization solutions. An interesting approach was proposed by Ping et al. [42], who developed a model predictive control (MPC) technique for the control of the heating process based on weather forecast compensation. MPC constitutes an advanced method of process control that is used to control a process while satisfying a set of constraints. The main advantage of MPC is the fact that it allows the current timeslot to be optimized, while taking future timeslots into account. The proposed system receives, in real-time, the indoor and ambient temperatures, as well as an ambient temperature forecast for future time-intervals, and appropriately adjusts the heat supply based on thermal comfort constraints and the modelling of the building's thermodynamics. Simulation results indicate that the delay of heating and the overheating of the space due to thermal inertia are limited, providing an overall better user experience regarding thermal comfort and eliminating the wasted energy consumed when the space is heated above the comfort level, which is most often the case when using more classical control approaches.

In most commercial systems using weather compensation, the temperature of the heating fluid is calculated as a function of some predetermined relation to the outdoor temperature called heating curve. This approach, however, often fails to capture the building's physics and conditions and cannot compute for future outdoor conditions, thus leading to an excess of energy consumption to maintain the users' thermal comfort. A convenient system of a non-invasive add-on module that can connect to existing heat controllers was developed using MPC to control the building's heating requirements [43]. The system was deployed during the 2013–2014 heating season in several locations, with the results being quite encouraging, achieving positive energy savings for all test sites.

A different approach is the use of data predictive control (DPC) methodologies, such as neural network prediction models and relevant machine learning algorithms. Data predictive control is a framework designed to combine the simplicity of model-based methods with the predictive capability of data-driven control. Using DPC algorithms, one can synthesize finite-horizon predictive control decisions after learning dynamical system models based on historical data. Of course, not all models are suitable for all problems, but they can be easily modified to serve similar purposes. In recent years, the introduction of controllers that are designed to house neural network models has increased the ability of locally processing information and decision making, allowing for more autonomy, advanced capabilities, and reliability. An example of such a controller was proposed in 2015 by Meng et al. [44]. The research team presented an improved version of the conventional PID neural network (PIDNN) control algorithm with additional momentum, which is used to improve its learning efficiency and solve the problem of local minimums, along with the introduction of an improved particle swarm optimization that helps initialize the weights of the neural network. The simulation was conducted via a multi-variable nonlinear coupling system and showed that the proposed algorithm displayed improvements in terms of regulating time and controlling precision compared to the original algorithm. Despite the fact that the presented controller approach is neither developed for, nor directly tested in, a boiler optimization scenario, the presented control methodologies can potentially be applied as an alternative for conventional boiler control methodologies. Smarra et al. [45] developed a data-driven control methodology based on random forests and regression trees, where an on-off biomass boiler was controlled in real-time, along with other sources of energy. The test cases, which contain both a simulated case and a real-world house scenario, displayed positive results, especially in the case of random forests. Macarulla et al. [46] introduced an adaptive control strategy targeted at commercial buildings with the help of feed-forward neural networks. The proposed system sends on/off commands to boilers at specific time intervals, attempting to minimize total consumption and the loss of user comfort at the same time.

Tsoumalis et al. proposed another DPC methodology where LSTM neural networks are used to predict the change in indoor temperature and the load of the boiler in the short-term (30-min look ahead), and a genetic algorithm (GA) was employed to obtain the optimal boiler configuration with regards to user thermal comfort and gas consumption minimization [47]. Results acquired from the trial in four real-world houses indicated a significant reduction in natural gas consumption with minimal comfort loss.

Table 1 summarizes the automated optimization/control methods presented in the literature.

Table 1. Automated optimization/control methodologies summary.

Ref. No.	Tools/Solvers Deployed	Control Target	Control Type (MPC/DPC)	Timeframe	Test Results
[42]	MPC based on time varying parameter state space model	Target water temperature of a house heating system	MPC (weather compensation)	Hourly	Simulation
[43]	MPC based on a building and a climate model	Thermostatic valves	MPC (weather compensation)	15-min	One house
[44]	Improved version of the basic PID neural network controller using particle swarm optimization	Any	DPC	-	Simulation
[45]	Random forests and regression trees	On-off biomass boiler, radiators	DPC	10-min intervals, 40-min horizon	Simulation and one house
[46]	Feed-forward neural networks	On-off gas boiler	DPC	15-min intervals	One commercial building
[47]	LSTM neural networks	Modulated gas boilers	DPC	5-min intervals, 30-min horizon	4 houses

Since automatic optimization usually involves minimal or no user interference, one aspect of significant importance is monitoring, which helps ensure that the system operates in nominal conditions and detects any problems or errors related to safety and performance. A paper published by a team at DELFT University describes a set of fault detection and diagnostic tools for condensing boilers [48]. The system was designed to use real-time measurements in order to evaluate performance degradation, making it ideal for building energy management systems that can store limited amounts of data. Through extensive simulations, the effectiveness of those tools was verified both in terms of quick fault detection, but also in isolating the source of the problem. Such systems contribute to making sure that boilers remain at an optimal operational level, and they can be integrated in an optimization system in order to provide more complete and production-ready solutions.

Though there are significant advancements in IoT technologies and quite a variety of methodologies have been explored, the transition to commercial applications seems to be quite slow. The transfer of research results to the market is a field of its own, which opens numerous subjects for investigation, including the validation of the derived conclusions in real life, as well as the impact from their massive application.

5. Gas Balancing Market

5.1. Introduction

The concept of demand response in the balancing market has been extensively visited in the electricity sector in the last few decades, where domestic and industrial customers are offered financial incentives to reduce or shift their electrical load [11]. Utilizing the latest technology available, electricity DR aggregators [49] can provide balancing services to the transmission system operator (TSO) in a "smart" and automated way, by shifting loads throughout the day while covering the user needs. In this way, they provide a financial benefit to the user and simultaneously balance services to the electricity TSO. The load curve is flattened by maintaining a smaller range between the peak and off-peak load during the day, and the balancing energy market attains more "depth" in terms of balancing resources, with the known positive effects in competition, price-setting, market power mitigation, and transmission/generation planning investments' deferral.

In the gas balancing market, DR has not been extensively utilized so far, despite the existence of automated optimization control solutions that have been implemented in the gas sector, as mentioned in Section 4. One main difference with the electricity sector is the lack of diversity in controllable loads, especially in the residential sector. Residential electricity consumers split their consumption among a variety of loads, which can be deferrable or controllable, while gas residential consumers mainly use gas for space heating and hot water exclusively, hence offering fewer potential applications. In addition, electricity smart metering infrastructure has been implemented at a larger scale compared to the gas metering infrastructure, especially for small- and medium-size consumers [50].

Despite the aforementioned setbacks, the value of DR solutions for the gas market is indisputable. Existing solutions for addressing high demand usually involve the upgrade of the existing pipeline, compressors, and control valve infrastructure, requiring costly operations, or, during extreme demand, the reliability of the whole system could be put in danger. Natural gas DR provides the capability to shift gas consumption and reduce peak gas demand, thus providing financially viable alternative methods of addressing the gas pipeline constraints, without the need of new or improved transportation infrastructure. Therefore, gas DR can have multifold objectives: (a) to minimize the overall system's cost by minimizing imbalance and (b) to shave peak load.

Gas load forecasting methodologies can be beneficial tools for developing gas balancing services. Due to the deviation between forecasted quantities/gas nominations and actual quantities, energy imbalances are created in the system, which are settled in the imbalance prices within the balancing market framework. Therefore, gas forecasting techniques, which can be utilized both by the system operators and by entities such as DR aggregators, can help in two ways: (a) they can improve the initial forecast, e.g., used for the day ahead scheduling of the gas transmission system and for defining a baseline consumption, and (b) they can define the dispatchable quantity that can be utilized at a later stage, e.g., in real-time, in order to respond to the balancing market prices (price-driven DR) or respond to a TSO peak-shaving event (event-driven DR). The above interactions are outlined in Figure 2.

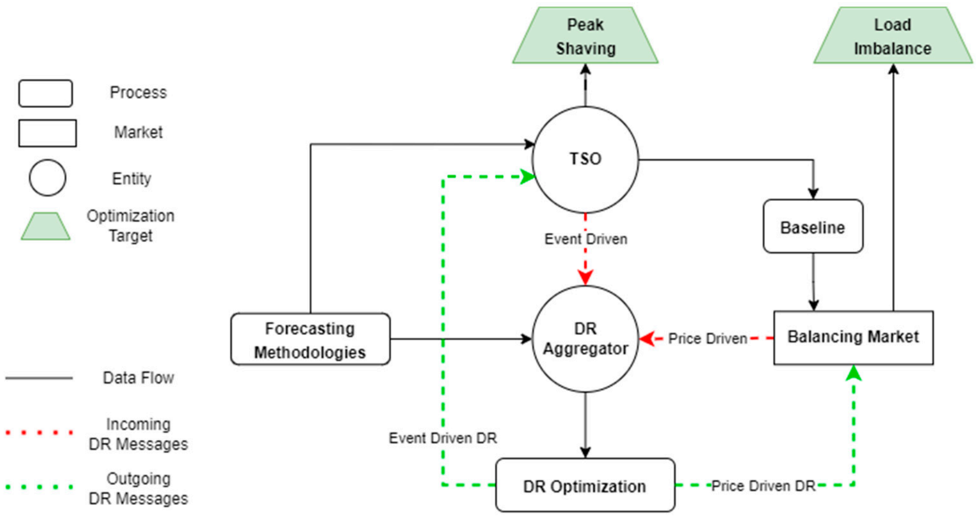

Figure 2. Interactions between the TSO and a DR aggregator entities in the DR process.

5.2. Gas Load Forecasting

The first issue encountered by gas suppliers in the gas market is the gas load forecasting for industrial, commercial, and residential consumers. Accurate forecasting is implicitly imposed by the regulatory framework with penalties in case of large forecasting errors, which mainly concern the short-term forecasts (day-ahead, intra-day, and real-time). In terms of long-term forecasting, the developed methodologies are mainly used for the long-term planning of the transmission system, e.g., for determining the required infrastructure upgrades. During the latest years, the evolution and advances in machine learning and big data technologies have provided a boost in the tools that can be utilized to increase forecasting accuracy, enabling novel methodologies to take advantage of more computational resources and complex data targeted at both short- and long-term forecasting.

Although, traditional approaches, such as time series analyses and regressions, are also applied and often result in sufficient prediction accuracy, requiring less computational resources and being generally less sensitive to under- and over-fitting. Such an approach was proposed by Potocnik and Govekar, who based their forecasting system on a stepwise regression method, implementing the selection and extraction of the most important input variables and features. The authors concluded that the performance of the model was sufficient in terms of top-level short-term forecasting requirements and internal optimization requirements, based on the results of the presented case study in the region of Ljubljana [51]. A logistic modelling approach was proposed by Shaikh and Ji in order to predict the mid- (2020) to long-term (2035) gas consumption in China [52]. The Levenberg–Marquardt Algorithm (LMA) was utilized to define the logistic model's parameters. Despite the simplicity of the proposed model, the attained results complied with studies performed by national and international institutions and scholars. Vitullo et al. outlined different methodologies regarding natural gas consumption forecasting, including linear models and neural networks, and provided an analysis of the most effective factors and data processing techniques used in commercial forecasting software [53]. They compared multiple linear regression, neural networks, and dynamic model adaptation in terms of generalization, interpolation, and extrapolation for this type of problem, emphasizing the inability of ANNs to predict on data that are unsimilar to the training data and the limited accuracy of the linear models. The results indicated that the combination of multiple linear regression with ANNs results in the best forecasting performance in most cases when considering the MAPE metric, and they exhibited that long-term forecasting requires different approaches compared to short-term, with generalization and extrapolation being a more significant requirement.

A widely used approach during the latest years in gas demand forecasting is neural networks. Common NN structures have been extensively utilized in the existing literature. Szoplik proposed a multilayer perceptron model that was trained and evaluated using consumption data from Szczecin (Poland) [54]. Other solutions evaluated less common NN architectures. For example, Akpinar et al. implemented an ABC-based neural network with a sliding window technique to produce a stable effective model, which forecasts the day-ahead gas consumption in Turkey [55]. The ABC algorithm is used as an alternative to back-propagation (BP) for determining the weights of the neural networks. For the examined problem, the ABC algorithm attains a much better forecasting accuracy performance in terms of the attained MAPE metric, with ABC resulting in 14.9% MAPE in the test set and BP in 30% MAPE. Furthermore, Ying et al. [56] proposed a hybrid forecast model, combining an autoregressive model and a convolutional neural network, in order to produce short-term forecasting of the hourly natural gas flows of 92 distribution nodes in the German network. Their model provided stable and accurate results for a variety of different types of nodes.

Apart from neural networks, other AI models have also been assessed. Wei et al. proposed the combination of a factor selection algorithm (FSA), a life genetic algorithm (LGA), and a support vector regression (SVR) in order to predict the gas consumption in three large cities of Greece [57]. The approach was compared to a respective ANN approach, a simple genetic algorithm (GA) with SVR and an LGA with SVR. The results showed the importance of LGA-SVR in the error rate reduction and the improvement that occurs when the dataset is divided into more sub-datasets for training.

Papageorgiou et al. developed a natural gas consumption forecasting day-ahead model using an adaptive neuro-fuzzy inference system (ANFIS) [58]. The authors initially reviewed existing approaches to similar problems, which are mainly based on ANNs, fuzzy cognitive maps (FCMs), and a combination of them, and they introduced a novel ANFIS approach. Their model was trained and inferred using historical natural gas consumption data from 10 cities in Greece, and its performance was compared to approaches based on the existing literature. The results indicated a better performance of the ANFIS approach. Another solution, focused on residential natural gas load forecasting, was presented by Uribe et al., who compared the performance of an ARIMA model to an SVM approach for the forecasting of the natural gas load in Medellín, Colombia [59]. The authors concluded that both models performed sufficiently well, with the ARIMA option providing faster inference and lower RMSE and MAE.

Table 2 summarizes the basic features of the research works in the literature on gas load forecasting and presents the difference in the methodologies employed when targeting short- compared to mid-/long-term forecasting.

Table 2. Gas load forecasting literature overview.

Ref. No.	Forecasting Methodology	Timestep	Lead-Time	Evaluation Metrics	Examined Test Case	Results
[51]	Stepwise regression	Hourly	Half hour and 24 h	Mean absolute range normalized error (MARNE)	Slovenian natural gas distribution company supply forecast	1.92–3.27%
[52]	Logistic model with Levenberg–Marquardt algorithm (LMA)	Yearly	-	Root mean square error (RMSE), mean absolute percentage error (MAPE), Mean absolute error (MAE), and R^2	China's natural gas demand long-term forecast (5–20 years ahead)	RMSE: 1.294–1.517 bn m^3 MAPE: 3.886–5.054% MAE: 1.604–2.691 R^2: 0.993–0.994 with an average out-of-sample value of 146.13 bn m^3
[53]	Multiple linear regression (LR), feed-forward neural network (ANN), combination of the above with the software GasDay^{TM} (GD)	Daily	Day-ahead	MAPE	GasDay^{TM} forecasting for 14 operating areas in US	Heating season: LR: 6.67–16.83% ANN: 6.33–16% GD: 5.21–14.47%
[54]	Feed-forward neural network	Hourly	-	MAPE	Gas demand forecast for Szczecin	8%
[55]	ABC-based neural network with sliding window	Daily	-	MAPE	Households and low-consuming commercial users' four-year consumption data	14.9%
[56]	Autoregressive model and a convolutional neural network	Hourly	Day-ahead	MAPE, normalized RMSE MARNE	92 distribution nodes in the German high-pressure gas pipeline network	MAPE: 10.7–14% nRMSE: 10.5–14 % MARNE: 5.7–7.7%

Table 2. *Cont.*

Ref. No.	Forecasting Methodology	Timestep	Lead-Time	Evaluation Metrics	Examined Test Case	Results
[57]	Factor selection algorithm (FSA), life genetic algorithm (LGA), and support vector regression (SVR)	Daily	Day-ahead	MAE, MAPE, RMSE, and MARNE	Three-year consumption data from three big cities in Greece (Athens, Thessaloniki, Larisa)	**Larisa** MAE: 0.17 GWh MAPE: 12.1% RMSE: 0.02 GWh MARNE: 2.12% with an average of approximately 2 GWh daily load **Thessaloniki** MAE: 1.27 GWh MAPE: 25.49% RMSE: 0.1 GWh MARNE: 3.62% with an average of approximately 12 GWh daily load **Athens** MAE: 1.59 GWh MAPE: 25.17% RMSE: 0.11 GWh MARNE: 4.24% with an average of approximately 13 GWh daily load
[58]	Adaptive neuro-fuzzy inference system (ANFIS)	Daily	Day-ahead	MSE, RMSE, MAE, MAPE, and R^2	Daily consumption data from 10 cities in Greece	MSE: 0.0007–0.0259 Normalized MWh^2 RMSE: 0.0271–0.1609 Normalized MWh MAE: 0.0176–0.1087 Normalized MWh MAPE: 6.223–36.717% R^2: 0.9839–0.5126
[59]	Autoregressive integrated moving average (ARIMA) and support vector machine (SVM)	Monthly	-	RMSE and MAE	Residential natural gas load in the municipality of Medellín, Antioquia, Colombia	**ARIMA** RMSE: 560,357.2 ft^3 MAE: 434,956.49 ft^3 **SVM** RMSE: 616.128,8 ft^3 MAE: 500.304,3 ft^3

5.3. Gas System Balancing

Gas TSOs are responsible for monitoring the transportation system in terms of nodal pressures and flows and for taking appropriate actions to keep the system stable. When the nodal pressures are low, a load reduction by gas loads could help restore the pressure to normal levels. Instead, when the pressures are high, an increase of gas consumption would be beneficial for the system. In both cases, the gas TSO executes auctions where upward and downward balancing gas is purchased and sold, respectively. Gas-consuming industries and gas DR aggregators can participate in such auctions and adjust their gas load to acquire additional profits.

The gas DR aggregator signs a flexibility contract with the consumer, under which the consumer follows specific instructions to increase or decrease its consumption in exchange for extra profits. This is possible either through manual notifications, which the consumers must follow by adjusting their load, or through direct automatic control of their heating systems, i.e., through automatic DR. This concept complies fully with the regulatory framework of European natural gas markets, where balancing service providers (BSPs) can participate in balancing energy auctions both for upwards and downwards balancing gas.

Gas DR can further optimize the natural gas consumption among a network's nodes, offering several benefits. As stated in the Introduction, the balancing of the daily load achieved through demand response techniques offers better exploitation of the existing pipeline infrastructure by limiting the peak load, and thus limiting or deferring the capital-intensive requirements of upgrading or building new pipeline, compressor, and/or storage solutions to uninterruptedly cover the gas demand. Despite its advantages, there are a few important restrictions (legal concerns and regulations) for adopting DR, as stated by the analysis of Gordon A. Coffee [60]. Specifically, the author raised the concern of the DR participants' unwillingness to shift their loads in an automatic fashion and the risk of switching to other energy sources to cover their comfort or functionality loss, such as electricity. Another concern is the pricing policy in the gas balancing market, where there is no compensation for gas savings with a concept similar to the "negawatt" used in electric DR, which represents unused energy. Finally, there is a problem determining whether gas suppliers or third parties would be the providers of the DR service, since the former do not have an incentive due to their lack of need to sell the excess capacity to gas-fired generators to achieve revenue, and the latter would be required to compensate the end users for their lost productivity in the case of commercial consumers or comfort levels in the case of residential ones. Such issues are mostly answered by Tsoumalis et al. [61], where the concept of automated gas DR with domestic gas boilers was introduced, providing the market design for gas DR, the baseline calculation methodology, and the modelling/algorithm process for the efficient participation of a gas consumer/gas DR aggregator in the gas balancing market to provide upward and downward balancing gas services to the gas TSO, while retaining the comfort of domestic residents.

Gas DR programs have been recently brought to the spotlight in the US by a bill sponsored by Senator Sheldon Whitehouse (D-RI) to "establish a natural gas demand response pilot program to use the latest demand response technology from the energy sector for natural gas.", leading the Department of Energy to evaluate the feasibility and potential of gas DR practices at a national level [62].

In this context, DR in natural gas has been applied in practice at regional levels in commercial solutions during the last few years, yielding interesting results. Southern California Gas Co. (SoCalGas) tested an energy efficiency program with the purpose of performing minor adjustments to their residential clients' heating schedules that would result in large overall savings. SoCalGas DR programs were implemented in three periods to this date: 2016–2017, 2017–2018, and 2019–2022. The incentive for the participant is a reward of bill credits. The results from the testing period (2018–2019) showed a significant decrease of the average load in both vendors that participated in the trial during the intra-day testing period, with the most important impact being noticed when DR was applied in the morning [63]. An important setback though was that, after the DR period ended, the load increased (snap-back event); hence, the overall daily average load was not significantly reduced.

Con Edison, who already implemented DR in the electricity sector, also decided to carry out a gas DR pilot for the period 2018–2021 as a main part of a program called "Smart Solutions" in the region of New York [64]. The main objectives of the pilot included the evaluation of the load reduction that can be achieved during a DR event over a 24-h window of the next day using measurement and verification (M&V) techniques, the engagement of the customers and their willingness to participate, and the collection of consumption data in order to draw conclusions over the effectiveness of the method and the possible integration with the load forecasting process. The test pilot was divided into three time periods with a duration of 1 year each. At the time of the writing of this paper, the results from the period 2018/19 were available and were used in order to define the changes for the 2019/20 period. In further detail, the best performance was achieved in commercial customers employing non-space heating curtailment strategies, with no valid conclusion drawn for the rest of the customers, including residential ones. In addition, it was noticed that some consumers switched to other sources such as fuel oil and other liquid fuels during the DR events, in spite of the prohibition imposed by the company. Finally, similarly to the case of SoCalGas, a snapback event was also observed, but the total realized daily load reduction was significant, as displayed by the period 2019/20 results [65].

Research work has also been performed in gas DR. Hu et al. discussed the existing technologies and challenges of gas DR implementation and proposed a mathematical model aimed at optimizing the peak household load while maintaining equitable comfort service [66]. The simulated results displayed a peak of up to 15% with minimal comfort loss. Prior research indicated that the most representative gas consumption comes from heating-related consumption. Montuori and Alcázar-Ortega estimated that the flexibility potential of district heating systems as gas aggregators is significant and assessed the benefits of the DR provision on the region of the Italian Peninsula [67]. The same authors used data from The Marches (Italy) to evaluate whether residential demand response can result in financial benefits both for the participating consumers and for the gas supplier(s) targeting the minimization of their daily imbalance costs (for each gas day) [68]. Monte Carlo simulations displayed that, through the participation of residential clients in the gas balancing market, the annual cost of the gas supply can be reduced by 15–20% for the consumer and the imbalance cost by up to 50% for the respective gas amount at the same time. Su et al. proposed a data-driven real-time pricing methodology for the demand management of a gas supply system [69]. The authors modeled a multi-objective optimization problem targeted at peak shaving, supply reliability improvement, gas supplier profit improvement, and the maintenance of customer's thermal comfort, use LSTM neural networks to forecast the system's behavior and apply GA to find the optimal price. Speake et al. examined the potential of residential gas DR during extreme cold weather events [70]. The authors simulated a total of eight DR strategies using data from the 2017–2018 winter of the north-east US and compared the results with consumption data acquired from a simulation targeted at the baseline consumption. The DR strategy simulations resulted in consumption savings ranging from 1% (attained from conservative strategies) up to 29% (attained from the most aggressive strategies). Ala-Kotila et al. evaluated the DR potential of the central heating system of existing residential apartments through the deployment of a DR system that utilized weather forecasts and installed sensor data [71]. The deployed system performed load reduction by measuring the domestic hot water (DHW) valve position and the temperature of the heating supply water. The system was tested on 27 residential real-world buildings, connected in eight distinct heating supply systems, and the results showed an average peak saving of up to 15% and an average energy consumption reduction of 11%.

Table 3 summarizes the main features of past research works on gas system balancing and the provision of DR by gas end-consumers.

5.4. Cross-Border Balancing

Within Europe, the European Network of Transmission System Operators for Gas (ENTSOG) proposed some guidelines to be followed by all European TSOs regarding the cross-zonal balancing of gas, among other directives requested by the European Commission (EC) [72]. Within the guidelines, three main models were proposed to be implemented by TSOs: (a) shipper-led cross border portfolio balancing, (b) cross border TSO balancing, and (c) joint balancing platform. The above guidelines constituted a draft network code, which was later materialized with the consultation of the European Union Agency of Cooperation of Energy Regulators (ACER) into the Network Code on Gas Balancing of Transmission Networks, accepted and published by EC on 26 March 2014 [73]. This regulation "*supports the development of a competitive short term wholesale gas market in the European Union that enables the provision of gas flexibility, from whatever source, to offer it for purchase and sale* via *market mechanisms so that network users can balance their balancing portfolios efficiently or the transmission system operator can use the gas flexibility when balancing the transmission net-*

work". The regulation set out common gas balancing rules, including network-related rules on nomination procedures, imbalance charges, settlement processes associated with the daily imbalance charge, and operational balancing between transmission system operators' networks. Concerning cross-border balancing, the regulation provisions that the gas TSOs can consider a joint balancing platform to be used for an adjacent balancing zones, where there is sufficient interconnection capacity. However, to the best of our knowledge, until now, no such platform has been constructed and operated by the gas TSOs in Europe.

Table 3. Gas system balancing and DR services by end-consumers overview.

Ref. No.	Methodology Deployed	Implicit /Explicit DR	Appliances Used For DR	Control Type	Timeframe	Evaluation Metrics	Test Results
[63]	Scenario-based constant target room temperature reduction	Implicit	Smart thermostats	Manual	Daily notifications, 5 AM to 9 AM or 5 PM to 9 PM	Average load reduction hourly impact percentage during the DR event	AM events: 15.21% PM events: 15.46%
[64,65]	Event triggered by the region's average outdoor temperature dropping below 18 °F	Implicit	Smart thermostats	Manual	Day-ahead notifications	Daily net load reduction	Average daily net load reduction from all events: 0.02 dekatherms/device, 56.1 dekatherms totally
[66]	Optimal control problem (OCP) based on physics constraints modelling	Explicit	Smart thermostats	Automatic	1-h and 3-h ahead	Peak demand reduction percentage	Peak demand reduction by 15% using the 3-h ahead model through simulations
[67]	Flexibility estimation using flexibility share per sectors evaluated in [68]	-	Residential, industrial, and commercial domestic heating loads	-	-	Flexibility potential per region (in GWh annually)	Flexibility is calculated at 1237 GWh per year (12.7% of the whole consumption)
[68]	Monte-Carlo simulations for the calculation of the flexible consumption per consumer's category	-	Residential, industrial, and commercial domestic heating loads	-	Hourly	Natural gas balancing price, total average daily gas cost for the consumer	15–20% cost reduction for the customer, 50% reduction of the imbalance cost for the involved amount of gas
[69]	LSTM for load forecasting and GA for the optimization of the natural gas price	-	Total system load	-	Hourly	Peak load reduction with the application of DSM through the determination of the price	6–7%
[70]	Pre-defined target indoor temperature setpoint scenarios	Implicit	Residential	Automatic	Hourly	Simulated total consumption	1% (conservative strategy) up to 29% (aggressive strategy)
[71]	Peak shaving through trigger based on DHW valve position and heating supply water temperature	Implicit	Residential	Automatic	10-min	Peak load and energy consumption reduction	Peak load: 14–15% Energy: 11%

Despite the establishment of this regulation, network users (NUs) across Europe did not always manage to adapt appropriately, exhibiting balancing misconduct. This situation has led ACER and ENTSOG to release new recommendations in 2021, including the exchange of balancing misconduct information across gas TSOs and national regulatory authorities (NRAs), targeting the minimization of the risks imposed by the deviations from the new regulatory framework [74].

6. Integrated Electricity and Gas Demand Response

With the evolution of the market characteristics of electricity and natural gas, new opportunities arise for the development of flexible solutions that can take advantage of the way these two resources affect each other, both through their domestic and industrial usage. Despite the fact that DR is currently mainly used in the electricity sector, the potential benefits of DR in natural gas, as outlined in the previous chapters, are numerous. Taking into consideration the fact that natural gas is also used in electricity production, a balancing service that optimizes both electricity and natural gas loads could aggregate the benefits to the energy providers in both sectors. At the same time, through the same solution, the domestic consumer can benefit both financially and in terms of user comfort, while industrial units can also receive financial incentives by participating in DR programs.

Sheikhi et al. introduced the smart energy hubs framework and proposed a system where residents can switch the source of energy between gas and electricity, in response to real-time gas and electricity price signals [75]. The selection is performed based on the Nash equilibrium methodology, and simulations show that financial benefits from IDR can be attained both for the supplier and the end consumer. Another Nash equilibrium-based methodology was proposed by Khazeni et al., where users can switch their energy source between energy retailers and from their own combined heat-power units (CHP) in order to cover their electricity and heating needs [76]. The proposed solution leads to a Nash equilibrium point from which neither retailers nor end users have financial incentives to deviate. Brahman et al. proposed a multi-objective optimization problem, incorporating electricity, natural gas, and solar radiation to cover the users' electricity and thermal needs [77]. The objectives of the system include the minimization of the total cost, the maintenance of user comfort, peak load curtailment through DR signals, and the reduction of the total emissions generated. The problem was formulated as a mixed integer linear programming (MILP) model and was solved using the CPLEX solver for the three simulated cases. Su et al. proposed an interval optimization method for the load scheduling of a domestic multi-energy system, including electricity and gas loads [78]. The authors modeled uncertainties using interval numbers and constraints using relaxation with tolerance degrees, transforming the problem to a deterministic one before applying a genetic algorithm to obtain the solution. Simulation results displayed significant cost savings compared to traditional approaches and sufficient robustness in terms of uncertainties. Shao et al. considered the optimization of integrated electricity and gas systems using IDR in energy hubs [79]. The authors considered both electricity and gas loads as flexible and controllable in the demand side and employed a two-level optimization framework to model the effect of IDR in energy hubs on the scheduling of the integrated electricity and gas system. The solution of the problem was performed by dividing the formulated TL-MINLP problem into two sub-problems, applying the Karush–Kuhn–Tucker (KKT) transformation and McCormick envelopes to each problem. The result was a standard MILP problem and a single-level nonlinear constraint optimization problem, both of which were solved more efficiently than the original TL-MINLP problem. Simulation results displayed that the application of IDR in energy hubs can significantly enhance the flexibility of the integrated electricity and gas system.

IDR has also been investigated in the industrial and commercial sectors. Dababneh and Li proposed an IDR optimization problem regarding the electricity and gas utilization during the manufacturing process solved using the modified simulated annealing (MSA) algorithm. The simulated cases tested the response of the manufacturer to the reception of real-time price signals from energy providers, and results displayed financial savings of up to 68% for the manufacturer. Liua et al. modeled the behavior of a load serving entity (LSE), which participates in the day-ahead multi-energy market for electricity, gas, and heat [80]. The entity can also store and convert energy using its own gas-fired CHP, electric boilers, heat pumps, or other appropriate equipment. The authors simulated cases both for each market independently and for all markets simultaneously, concluding that IDR in the multi-energy market provides benefits both to the entity and to the network by reducing peak loads. In addition, Maeder et al. [81] investigated flexibility technologies for decarbonized power systems and applied a novel optimization model in various power systems in Central Europe (Switzerland, Austria, France, Germany, and Italy). The authors concluded that decarbonized power systems entail a cost shift from the operational to the investment phase, and total normalized costs could be higher than power market prices.

In terms of power generation, due to the low cost and emissions of natural gas, the usage of natural gas-fired power plants has been steadily increasing during the last years, gaining significant share over oil and coal sources [82]. This fact provided the incentive for new optimization models to be developed, which simulate both the natural gas and the electricity infrastructures. Such an approach was detailed by Bai et al. [83], where a case study was performed on a six-bus electricity network, containing electricity loads, gas-fired generators, and wind turbines, along with a seven-node gas network simulating different wind uncertainty levels in order to evaluate the feasibility and effects of a co-optimization strategy. During the case study, models were developed that considered both system's parameters and constraints in detail, and a DR program was evaluated in terms of providing aggregated benefits. Finally, the approach was tested in a larger system simulation comprised by a 118-bus electricity network with a 14-node natural gas network (compared to the 7-node system of the initial test case), in order to evaluate the practical value in bulk systems. The results of the test case indicated a decrease in the total operational costs in all cases where a combined gas–electricity DR was implemented. Additionally, the simulation in the larger system yielded similar results and within an acceptable computation time.

Another approach based on the same advantages of natural gas was proposed by Zhang et al. [84], which aimed to coordinate natural gas and electricity networks in order to result in a less volatile hourly electric load profile. The proposed model took into consideration random outages of generating units and transmission lines, random errors in the forecasting of the day-ahead electricity loads, as well as natural gas network constraints that affect gas-fired generating units in a stochastic approach. Monte Carlo simulations were carried out to cover multiple scenarios. The authors concluded that hourly demand response and the coordination of the two systems helped reduce the operation costs by resulting in a flat electric load profile. This DR approach does not consider residential natural gas DR.

Wang et al. reviewed the concepts of "Energy Internet", multi-energy systems, and integrated demand response, which combined multiple energy sources such as electricity, natural gas, and thermal energy into a unified DR program, that took into account the interaction of the sources and the user's comfort, hence considering residential gas usage [12]. The advantages of the integrated DR over the traditional electricity DR practices were outlined. The authors concluded that multi-energy systems, which are comprised of electricity, thermal energy, natural gas, and other forms of energy, help users maintain their comfort by shifting their energy source instead of shifting their loads. This means that even inelastic loads can participate in such DR programs. In terms of domestic heating, the combination of electricity and natural gas can lead to covering the same loads by assigning a larger portion of the needed energy to natural gas when electricity prices are high and maintaining the comfort level partially based on the buildings' thermal inertia. In a similar fashion, when, for instance, the wind output is high and the cost of electrical energy is low, the source of energy can be switched to electricity and elastic loads can be served. In this way, the difference from peak to valley of the electric load can be reduced.

Table 4 summarizes the main features of the research works in the literature of integrated demand response in multi-energy systems.

Table 4. Integrated demand response literature overview.

Ref. No.	Tools/Solvers Deployed	DR Target	Problem Definition	Appliances Used for DR	Timeframe	Test Case
[75]	Distributed algorithm for the determination of the system's Nash equilibrium	Decrease of total energy cost by electrical and gas load shifting	Electricity and gas	Micro gas turbines	Day-ahead execution	Simulation
[76]	Epsilon Nash equilibrium approximation through a novel discretization algorithm	Increase of energy retailers' profits, decrease of customers' payments	Electricity and heat	Non-deferrable electric and heating loads	Day-ahead execution	Simulation
[77]	Multi-objective optimization solved through the epsilon constraint method	Decrease of the total energy cost	Electricity, gas, and heating storage	Household appliances, production, and storage components	Hour-ahead	Simulation
[78]	Interval optimization modelling and solution through genetic algorithm	Switching between electricity and gas consumption	Electricity and gas	Water heater, kitchen stove, clothes washer, air-conditioning	Two-days ahead optimization	Simulation
[79]	Solution of an MINLP problem through MILP transformation via the Karush–Kuhn–Tucker (KKT) transformation and McCormick envelopes	Total electricity and gas system cost optimization	Electricity and gas	Electrical and gas loads in energy hubs	Hourly	Simulation
[80]	Modified simulated annealing (MSA) algorithm	Decrease of total energy cost by electrical and gas load shifting	Electricity and gas	Industrial electricity/gas load	Real-time control to act in 15–30 min	Simulation
[81]	Power system optimization model to determine the cost-efficient deployment	Total systems behavior and flexibility resources evaluation	Electricity and gas	Power systems in Central Europe	Long-term evaluation in decades	Simulation
[83]	Interval-based nonlinear optimization	Total electricity and gas system cost optimization	Electricity and gas	Electricity loads, residential gas loads	Hourly	Simulation
[84]	Short-term stochastic non-linear model transformed into MILP through linear approximation	Gas-fired units consumption profile flattening	Electricity	Electricity loads	Day-ahead	Simulation

7. Conclusions and Future Research Directions

Climate change has been a topic of high interest during the last years, with greenhouse gas emissions being one/of the major factor behind the augmentation of the phenomenon. Multiple initiatives for achieving emission reduction targets have been introduced by countries worldwide, with energy efficiency being a major aspect towards this direction. One of the most important emission sources is natural gas, a fossil fuel adopted by most countries worldwide utilized in various applications, including the residential sector.

First, the initial step towards energy efficiency was improvement in boiler technology. The most important solution at the design phase was the introduction of condensing boilers, which exhibit a significant increase in combustion efficiency compared to conventional boilers. Other solutions include the usage of hydrogen together with natural gas during the combustion process.

Second, after the boiler's design phase and before its operation phase, manual optimization can be employed to determine the boiler's optimal operating parameters through the mathematical modelling of its efficiency.

Third, at the boiler operating phase, technological advancements in the fields of smart homes, machine learning, and Internet of Things have created opportunities for the development of optimization solutions targeted at improving natural gas consumption energy efficiency, yielding significant potential financial and environmental advantages. Specifically, automated optimization has been applied in pilot projects, requiring minimal human intervention, to ensure optimal real time boiler operation. Additionally, various MPC- and DPC-based solutions have been proposed in the literature that either use the boiler's and building's mathematical models or utilize data acquired from sensors for the development of machine learning models (such as neural networks), in order to forecast the boiler's efficiency and building's thermal behavior and provide control instructions accordingly.

These methodologies, apart from directly improving the efficiency of the boiler, can also be utilized to shape solutions adjusted to the gas balancing market, including natural gas demand response. Combined with gas load forecasting techniques, where the existing literature is vast, automated optimization solutions can be used in order to control the natural gas load in real-time and provide implicit or explicit demand response services. The existing literature does not currently cover the gas DR concept sufficiently, despite its great potential, with only two large-scale pure gas DR real-world pilot tests/trials existing currently and a small number of research works, most of which were validated through simulated test cases. Considering the success of the already existing pilot tests, there is certainly room for more similar trials that can focus on automated DR solutions. Despite the existing literature, there is an apparent lack of practical commercial approaches in gas DR, since many issues/challenges need to be explored and resolved; to this end, more large-scale DR pilots would definitely be beneficial.

However, the concept of integrated demand response has been more extensively covered in the existing literature, providing DR solutions that combine natural gas along with other energy sources, such as electricity and heat, and displaying promising results in terms of financial benefits from the combined DR services provision. However, similar to gas DR, there is still a lack of commercial solutions, despite the promising results of existing research works in the literature, and no large-scale real-world pilots have been performed so far.

Based on the above conclusions, Table 5 summarizes the critical issues that have already been solved and the main challenges that remain unresolved, and it provides useful insights to where the current research and development are heading.

Table 5. Critical issues, main challenges, and insights for the way forward.

Timeframe	Research Areas	Critical Issues That Have Been Solved	Main Challenges That Remain Unsolved	Insights to Where the Current Research, Development, and Application Are Heading
Gas boilers design phase	Combustion process	✓ Modulated load in the place of on-off boilers ✓ Introduction of condensing boilers	✓ Further energy efficiency improvement	✓ Mix of gases with different compositions to achieve higher combustion efficiency ✓ Use of different materials as boiler components
After the boiler's design phase and before its operation phase	Combustion and fuel-mix optimization	✓ Upgrading of a conventional boiler to a condensing one ✓ Improvement of the flammable mix	✓ Proper maintenance and fault detection	✓ Data-predictive methodologies for the definition of the boiler's functional parameters before commissioning ✓ Data-predictive methodologies for early fault detection and improvement of their generalization to assist in their robustness and real-world adoption ✓ public adoption of automated fault detection solutions
	Energy efficiency—gas consumption minimization	✓ Development of automated optimization solutions based on MPC and DPC methodologies	✓ Public adoption of automated optimization solutions	✓ DPC methodologies utilizing the latest advancements in AI seem to take over more traditional MPC approaches ✓ Utilization of the advancements in IoT technology to commercialize existing solutions
Boiler operating phase	Gas demand response	✓ Establishment of pilot DR programs that validate the meaning of gas DR ✓ Assessment of residential gas DR potential through simulations	✓ Large-scale adoption of gas DR programs ✓ Residents' willingness to participate in manual gas DR events	✓ Research is heading towards automated gas DR in smaller installations (i.e., domestic gas boilers), attempting to mitigate residents' unwillingness to participate in manual DR event ✓ More automated gas DR pilots with large number of domestic gas boilers ✓ Setup of commercial companies with automated gas DR solutions (ICT, optimization algorithms, etc.) ✓ Commercial commencement of gas DR applications with domestic boilers
	Integrated demand response	✓ Validation of the aggregated advantages of multiple sources of DR services through simulated environments ✓ Multiple combinations of energy sources (gas, electricity, heat, etc.) have been assessed in the existing literature, yielding promising results	✓ Large-scale real-world adoption of IDR solutions is non-existent	✓ Transfer of theoretical IDR concepts to practical implementations and real-world testing ✓ Public adoption through commercialization of more practical approaches

Author Contributions: Conceptualization, G.I.T., Z.N.B., G.V.C. and P.N.B.; methodology, G.I.T., Z.N.B., G.V.C. and P.N.B.; resources, G.I.T., Z.N.B. and G.V.C.; writing—original draft preparation, G.I.T., Z.N.B., G.V.C. and P.N.B.; writing—review and editing, G.I.T., Z.N.B., G.V.C. and P.N.B.; visualization, G.I.T., Z.N.B. and G.V.C.; supervision, P.N.B.; project administration, P.N.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

ABC	Artificial bee colony
ACER	European Union Agency of Cooperation of Energy Regulators
ANFIS	Adaptive neuro-fuzzy inference system
ARIMA	Autoregressive integrated moving average
CCGT	Combined-cycle gas turbine
CHP	Combined heat-power
CNG	Compressed natural gas
DHW	Domestic hot water
DPC	Data predictive control
DR	Demand response
ENTSOG	European Network of Transmission System Operators for Gas
EU	European Union
FCMs	Fuzzy cognitive maps
FSA	Factor selection algorithm
GA	Genetic algorithm
GHG	Greenhouse gas
ICT	Information and communications technology
IDR	Integrated demand response
KKT	Karush–Kuhn–Tucker
LDC	Local distribution company
LGA	Life genetic algorithm
LSTM	Long-short term memory
M&V	Measurement and verification
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MARNE	Mean absolute range normalized error
MILP	Mixed integer linear programming
MINLP	Mixed integer non-linear programming
MPC	Model predictive control
MSA	Modified simulated annealing
NANGAM	North American Natural Gas Model
NN	Neural network
NU	Network user
TSO	Transmission system operator

References

1. Paraschiv, S.; Paraschiv, L.S. Trends of carbon dioxide (CO_2) emissions from fossil fuels combustion (coal, gas and oil) in the EU member states from 1960 to 2018. In Proceedings of the 7th International Conference on Energy and Environment Research (ICEER)—Driving Energy and Environment in 2020 towards a Sustainable Future, Porto, Portugal, 14–18 September 2020.
2. Abas, N.; Kalair, A.; Khan, N. Review of fossil fuels and future energy technologies. *Energy* **2015**, *85*, 208–220. [CrossRef]
3. Thomson, H.; Snell, C.; Bouzarovski, S. Health, Well-Being and Energy Poverty in Europe: A Comparative Study of 32 European Countries. *Int. J. Environ. Res. Public Health* **2017**, *14*, 584. [CrossRef] [PubMed]
4. Dutta, R. Use of Clean, Renewable and Alternative Energies in Mitigation of Greenhouse Gases. In *Encyclopedia of Renewable and Sustainable Materials*; Elsevier: Amsterdam, The Netherlands, 2020.
5. Burnham, A.; Han, J.; Clark, C.; Wang, M.; Dunn, J.B.; Palou-Rivera, I. Life-Cycle Greenhouse Gas Emissions of Shale Gas, Natural Gas, Coal. *Environ. Sci. Technol.* **2011**, *46*, 619–627. [CrossRef] [PubMed]
6. Chen, Y.; Li, J.; Lu, H.; Xia, J. Tradeoffs in water and carbon footprints of shale gas, natural gas, and coal in China. *Clean Technol. Environ. Policy* **2021**, *23*, 1385–1388. [CrossRef]
7. United Nations. Paris Agreement. 2015. Available online: https://unfccc.int/files/essential_background/convention/application/pdf/english_paris_agreement.pdf (accessed on 6 January 2022).
8. Capros, P.; Kannavou, M.; Evangelopoulou, S.; Petropoulos, A.; Siskos, P.; Tasios, N.; Zazias, G.; DeVita, A. Outlook of the EU energy system up to 2050: The case of scenarios prepared for European Commission's "clean energy for all Europeans" package using the PRIMES model. *Energy Strategy Rev.* **2018**, *22*, 255–263. [CrossRef]

9. Clean Energy for All Europeans Package. 2019. Available online: https://ec.europa.eu/energy/topics/energy-strategy/clean-energy-all-europeans_en (accessed on 6 January 2022).
10. European Commission. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. 14 July 2021. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52021DC0550&from=EN (accessed on 6 January 2022).
11. Jordehi, A.R. Optimisation of demand response in electric power systems, a review. *Renew. Sustain. Energy Rev.* **2019**, *103*, 308–319. [CrossRef]
12. Wang, J.; Zhong, H.; Z, M.; Xia, Q.; Kang, C. Review and prospect of integrated demand response in the multi-energy system. *Appl. Energy* **2017**, *202*, 772–782. [CrossRef]
13. European Commission. 2030 Climate & Energy Framework. EU. 2014. Available online: https://ec.europa.eu/clima/policies/strategies/2030_en (accessed on 6 January 2022).
14. EU. 2050 Long-Term Strategy. 2018. Available online: https://ec.europa.eu/clima/policies/strategies/2050_en (accessed on 4 July 2020).
15. EU. Directive (EU) 2018/844 of the European Parliament and of the Council of 30 May 2018 Amending Directive 2010/31/EU on the Energy Performance of Buildings and Directive 2012/27/EU on Energy Efficiency (Text with EEA Relevance). 2018. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018L0844&from=EN (accessed on 6 January 2022).
16. European Commission. Secure, Clean and Efficient Energy | Horizon 2020. Available online: https://ec.europa.eu/programmes/horizon2020/en/h2020-section/secure-clean-and-efficient-energy (accessed on 6 January 2022).
17. Odysee-Mure. Germany | Energy Profile. May 2021. Available online: https://www.odyssee-mure.eu/publications/efficiency-trends-policies-profiles/germany-country-profile-english.pdf (accessed on 6 January 2022).
18. United Nations. Paris Agreement—Status of Ratification. Available online: https://unfccc.int/process/the-paris-agreement/status-of-ratification (accessed on 7 May 2020).
19. Range Heating, Designing Buildings Wiki. Available online: https://www.designingbuildings.co.uk/wiki/Types_of_domestic_heating_system (accessed on 11 May 2020).
20. Persson, U.; Werner, S. *Quantifying the Heating and Cooling Demand in Europe*; EU, 2015; Available online: https://heatroadmap.eu/wp-content/uploads/2018/09/STRATEGO-WP2-Background-Report-4-Heat-Cold-Demands.pdf (accessed on 11 May 2020).
21. Vignali, G. Environmental assessment of domestic boilers: A comparison of condensing and traditional technology using life cycle assessment. *J. Clean. Prod.* **2017**, *142*, 2493–2508. [CrossRef]
22. Aste, N.; Adhikari, R.S.; Compostella, J.; Pero, C.D. Energy and environmental impact of domestic heating in Italy: Evaluation of National NOx emissions. *Energy Policy* **2013**, *53*, 353–360. [CrossRef]
23. Brkic, D.; Tanaskovic, I. Systematic approach to natural gas usage for domestic heating in urban areas. *Energy* **2008**, *33*, 1738–1753. [CrossRef]
24. Shipton's, Heating & Cooling Ltd. Available online: https://shiptons.ca/shiptons-blog/a-brief-history-of-home-heating/21 (accessed on 11 May 2020).
25. Lazzarin, R.M. The importance of the modulation ratio in the boilers installed in refurbished buildings. *Energy Build.* **2014**, *75*, 43–50. [CrossRef]
26. Balanescu, D.T.; Homutescu, V.M. Experimental investigation on performance of a condensing boiler and economic evaluation in real operating conditions. *Appl. Therm. Eng.* **2018**, *143*, 48–58. [CrossRef]
27. Liu, F.; Zheng, L.; Zhang, R. Emissions and thermal efficiency for premixed burners in a condensing gas boiler. *Energy* **2020**, *202*, 117449. [CrossRef]
28. Specchia, S.; Toniato, G. Natural gas combustion catalysts for environmental-friendly domestic burners. *Catal. Today* **2009**, *147*, S99–S106. [CrossRef]
29. Xin, Y.; Wang, K.; Zhang, Y.; Zeng, F.; He, X.; Takyi, S.A.; Tontiwachwuthikul, P. Numerical Simulation of Combustion of Natural Gas Mixed with Hydrogen in Gas Boilers. *Energies* **2021**, *14*, 6883. [CrossRef]
30. Näslund, M. Combustion Control in Domestic Gas Appliances. Project Report. April 2014. Available online: https://arkiv.dgc.dk/sites/default/files/filer/publikationer/R1401_combustion_domestic_appliances.pdf (accessed on 11 May 2020).
31. Vanwormer, C.; Grassl, D. Best Practices for Condensing Boilers. *Ashrae J.* **2018**, *60*, 18–26.
32. Jones, D. Principals of Condensing Boiler System Design. *ASHRAE Trans.* **2014**, *120*, 1–8.
33. Kovacevic, M.; Lambic, M.; Radovanovic, L.; Pekez, J.; Ilic, D.; Nikolic, N.; Kucora, I. Increasing the efficiency by retrofitting gas boilers into a condensing heat exchanger. *Energy Sources Part B Econ. Plan. Policy* **2017**, *12*, 470–479. [CrossRef]
34. Cauchi, N.; Macek, K.; Abate, A. Model-based predictive maintenance in building automation systems with user discomfort. *Energy* **2017**, *138*, 306–315. [CrossRef]
35. Agarwal, S.; Suhane, A. Study of Boiler Maintenance for Enhanced Reliability of System A Review. *Mater. Today Proc.* **2017**, *4*, 1542–1549. [CrossRef]
36. Sridharan, S.; Mangalam, S. Carbon monoxide risks and implications on maintenance-intensive fuel-burning appliances—A regulatory perspective. In Proceedings of the 2017 Annual Reliability and Maintainability Symposium (RAMS), Orlando, FL, USA, 23–26 January 2017.
37. Shohet, R.; Kandil, M.S.; Wang, Y.; McArthur, J. Fault detection for non-condensing boilers using simulated building automation system sensor data. *Adv. Eng. Inform.* **2020**, *46*, 101176.

38. Wu, J.-T.; Zhang, Y.-B.; Xu, G.-S.; Lin, Y.; Lv, X.-G. Research on the Optimization of Boiler Efficiency based on Artificial Bee Colony Algorithm. *Comput. Inf. Sci.* **2014**, *7*, 30. [CrossRef]
39. Arash, B.; David, A.; Kevin, J.L.; Ehab, F.; Dennis, L.L. Measuring the potential of zonal space heating controls to reduce energy use in UK homes: The case of un-furbished 1930s dwellings. *Energy Build.* **2015**, *92*, 29–44.
40. Tronchin, L.; Manfren, M.; Tagliabue, L.C. Optimization of building energy performance by means of multi-scale analysis—Lessons learned from case studies. *Sustain. Cities Soc.* **2016**, *27*, 296–306. [CrossRef]
41. Nguyen, T.H.; Toroghi, S.H.; Jacobs, F. Automated Green Building Rating System for Building Designs. *J. Archit. Eng.* **2016**, *22*, A4015001. [CrossRef]
42. Ping, J.; Chenxi, J.; Shi, L.; Wenxue, X.; Yu, Q. Model Predictive Control of Heating Process with Weather Forecast Compensation. In Proceedings of the 2019 IEEE Symposium Series on Computational Intelligence (SSCI), Xiamen, China, 6–9 December 2019.
43. Lindelöf, D.; Afshari, H.; Alisafaee, M.; Biswas, J.; Caban, M.; Mocellin, X.; Viaene, J. Field tests of an adaptive, model-predictive heating controller for residential buildings. *Energy Build.* **2015**, *99*, 292–302. [CrossRef]
44. Meng, L.; Zou, Z.; Wang, Z.; Gui, X.; Yu, M. Design of An Improved PID Neural Network Controller based on Particle Swarm Optimazation. In Proceedings of the 2015 Chinese Automation Congress (CAC), Wuhan, China, 27–29 November 2015.
45. Smarra, F.; Jain, A.; Rubeis, T.d.; Ambrosini, D.; D'Innocenzo, A.; Mangharam, R. Data-driven model predictive control using random forests for building energy optimization and climate control. *Appl. Energy* **2018**, *226*, 1252–1272. [CrossRef]
46. Macarulla, M.; Casals, M.; Forcada, N.; Gangolells, M. Implementation of predictive control in a commercial building energy management system using neural networks. *Energy Build.* **2017**, *151*, 511–519. [CrossRef]
47. Tsoumalis, G.; Bampos, Z.; Chatzis, G.; Biskas, P.; Keranidis, S. Minimization of natural gas consumption of domestic boilers with convolutional, long-short term memory neural networks and genetic algorithm. *Appl. Energy* **2021**, *299*, 117256.
48. Baldi, S.; Quang, T.L.; Holub, O.; Endel, P. Real-time monitoring energy efficiency and performance degradation of condensing boilers. *Energy Convers. Manag.* **2017**, *136*, 329–339. [CrossRef]
49. Hansen, T.M.; Roche, R.; Suryanarayanan, S.; Maciejewski, A.A.; Siegel, H.J. Heuristic Optimization for an Aggregator-Based Resource Allocation in the Smart Grid. *IEEE Trans. Smart Grid* **2015**, *6*, 1785–1794. [CrossRef]
50. The Brattle Group. Demand Response for Natural Gas Distribution—Opportunities and Challenges. June 2018. Available online: https://www.brattle.com/wp-content/uploads/2021/05/13929_demand_response_for_natural_gas_distribution.pdf (accessed on 1 March 2022).
51. Potocnik, P.; Govekar, E. Applied short-term forecasting for the Slovenian natural gas market. In Proceedings of the 2016 13th International Conference on the European Energy Market (EEM), Porto, Portugal, 6–9 June 2016.
52. Shaikh, F.; Ji, Q. Forecasting natural gas demand in China: Logistic modelling analysis. *Int. J. Electr. Power Energy Syst.* **2016**, *77*, 25–32. [CrossRef]
53. Vitullo, S.; Brown, R.H.; Corliss, G.F.; Marx, B.M. Mathematical Models for Natural Gas Forecasting. *Can. Appl. Math. Q.* **2009**, *17*, 1005–1013.
54. Szoplik, J. Forecasting of natural gas consumption with artificial neural networks. *Energy* **2015**, *85*, 208–220.
55. Akpinar, M.; Adak, M.; Yumusak, N. Day-Ahead Natural Gas Demand Forecasting Using Optimized ABC-Based Neural Network with Sliding Window Technique: The Case Study of Regional Basis in Turkey. *Energies* **2017**, *10*, 781.
56. Ying, C.; Xiuqin, X.; Thorsten, K. Day-ahead high-resolution forecasting of natural gas demand and supply in Germany with a hybrid model. *Appl. Energy* **2020**, *262*, 114486.
57. Wei, N.; Li, C.; Li, C.; Xie, H.; Du, Z.; Zhang, Q.; Zeng, F. Short-Term Forecasting of Natural Gas Consumption Using Factor Selection Algorithm and Optimized Support Vector Regression. *J. Energy Resour. Technol.* **2018**, *141*, 032701. [CrossRef]
58. Papageorgiou, K.; Papageorgiou, E.I.; Poczeta, K.; Bochtis, D.; Stamoulis, G. Forecasting of Day-Ahead Natural Gas Consumption Demand in Greece Using Adaptive Neuro-Fuzzy Inference System. *Energies* **2020**, *13*, 2317. [CrossRef]
59. Uribe, G.J.G.; Guevara, D.E.R.; Gallego, P.A.R. Estimation of residential natural gas consumption in Medellín-Antioquia. *IEEE Lat. Am. Trans.* **2018**, *16*, 819–822. [CrossRef]
60. Coffee, G.A. Gas Demand Response Programs Are Alluring but Impractical. 21 September 2016. Available online: https://www.law360.com/articles/841747/gas-demand-response-programs-are-alluring-but-impractical (accessed on 2 July 2020).
61. Tsoumalis, G.; Bampos, Z.; Biskas, P.; Keranidis, S.; Symeonidis, P.; Voulgarakis, D. A novel system for providing explicit Demand Response from domestic natural gas boilers. *Appl. Energy* **2022**, *317*, 119038. [CrossRef]
62. Senator Sheldon Whitehouse, S.2649—Energy Infrastructure Demand Response Act of 2018. 4 November 2018. Available online: https://www.congress.gov/bill/115th-congress/senate-bill/2649 (accessed on 2 July 2020).
63. Bell, E.; Bieler, S.; Lehman, T.; Cain, N. 2018–2019 Winter Load Impact Evaluation of SoCalGas Smart Therm Program. 24 October 2019. Available online: http://www.calmac.org/publications/SoCalGas_2019_DR_Evaluation_Report_-_PUBLIC_FINAL.pdf (accessed on 3 March 2022).
64. Consolidated Edison Company of New York, Inc. Gas Demand Response Pilot Implementation Plan, 2018–2021. 1 July 2019. Available online: https://www.coned.com/-/media/files/coned/documents/save-energy-money/rebates-incentives-tax-credits/smart-usage-rewards/gas-demand-response-implementation-plan.pdf (accessed on 2 July 2020).
65. Consolidated Edison Company of New York, Inc. Gas Demand Response Report on Pilot Performance—2019/2020. 1 July 2020. Available online: https://documents.dps.ny.gov/public/Common/ViewDoc.aspx?DocRefId=%7B7FA119BD-B04D-4378-95A3-BB26697815AC%7D (accessed on 3 March 2022).

66. Fuyu, H.; Kaarthik, S.; Shriram, S.; Russell, B. Demand Response for Natural Gas: Technologies, Mathematical Models, and Challenges Ahead. 2021. Available online: https://arxiv.org/abs/2104.03269v2 (accessed on 8 June 2021).
67. Montuori, L.; Alcázar-Ortega, M. District Heating as Demand Response Aggregator: Estimation of the Flexible Potential in the Italian Peninsula. *Energies* **2021**, *14*, 7052.
68. Montuori, L.; Alcázar-Ortega, M. Demand response strategies for the balancing of natural gas systems: Application to a local network located in The Marches (Italy). *Energy* **2021**, *225*, 120293.
69. Su, H.; Ziob, E.; Zhanga, J.; Chia, L.; Lia, X.; Zhanga, Z. A systematic data-driven Demand Side Management method for smart natural gas supply systems. *Energy Convers. Manag.* **2019**, *185*, 368–383. [CrossRef]
70. Speake, A.; Donohoo-Vallett, P.; Wilson, E.; Chen, E.; Christensen, C. Residential Natural Gas Demand Response Potential during Extreme Cold Events in Electricity-Gas Coupled Energy Systems. *Energies* **2020**, *13*, 5192. [CrossRef]
71. Ala-Kotila, P.; Vainio, T.; Heinonen, J. Demand Response in District Heating Market—Results of the Field Tests in Student Apartment Buildings. *Smart Cities* **2020**, *3*, 157–171. [CrossRef]
72. ENTSOG. Gas Balancing Launch Documentation BAL0125-11. 2011. Available online: https://www.entsog.eu/sites/default/files/files-old-website/publications/Balancing/2011/BAL0125-11_Launch_Documentation.pdf (accessed on 1 December 2021).
73. European Commission. COMMISSION REGULATION (EU) No 312/2014 of 26 March 2014 Establishing a Network Code on Gas Balancing of Transmission Networks. 26 March 2014. Available online: https://documents.acer.europa.eu/en/Gas/Framework%20guidelines_and_network%20codes/Documents/EC%20reg%20NO%20312-2014%20BAL%20NC.pdf (accessed on 1 December 2021).
74. ACER & ENTSOG. ACER/ENTSOG Recommendations on Suspected Misconduct at EU Balancing Zones. 10 February 2021. Available online: https://extranet.acer.europa.eu/Official_documents/Position_Papers/Position%20papers/EU%20Balancing%20Suspected%20Misconduct_%20ACER_%20ENTSOG_Policy%20Paper.pdf (accessed on 1 December 2021).
75. Sheikhi, A.; Bahrami, S.; Ranjbar, A.M. An autonomous demand response program for electricity and natural gas networks in smart energy hubs. *Energy* **2015**, *89*, 490–499.
76. Khazeni, S.; Aras, S.; Rayati, M.; Soleymani, S.; Ranjbar, A.M. Retail Market Equilibrium in Multicarrier Energy Systems: A Game Theoretical Approach. *IEEE Syst. J.* **2018**, *13*, 738–747.
77. Brahman, F.; Brahman, F.; Jadid, S. Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system. *Energy Build.* **2015**, *90*, 65–75.
78. Su, Y.; Zhou, Y.; Tan, M. An interval optimization strategy of household multi-energy system considering tolerance degree and integrated demand response. *Energy* **2019**, *260*, 114144. [CrossRef]
79. Shao, C.; Ding, Y.; Siano, P.; Song, Y. Optimal Scheduling of the Integrated Electricity and Natural Gas Systems Considering the Integrated Demand Response of Energy Hubs. *IEEE Syst. J.* **2020**, *15*, 4545–4553.
80. Liua, P.; Dinga, T.; Zoub, Z.; Yang, Y. Integrated demand response for a load serving entity in multi-energy market considering network constraints. *Appl. Energy* **2019**, *250*, 512–529. [CrossRef]
81. Mattia, M.; Olga, W.; Konstantinos, B. Assessing the need for flexibility technologies in decarbonized power systems: A new model applied to Central Europe. *Appl. Energy* **2021**, *282*, 116050.
82. International Energy Agency (IEA) via the World Bank. World Development Indicators, the World Bank. 2020. Available online: https://databank.worldbank.org/source/world-development-indicators (accessed on 5 May 2021).
83. Bai, L.; Li, F.; Cui, H.; Jiang, T.; Sun, H.; Zhu, J. Interval optimization based operating strategy for gas-electricity integrated energy systems considering demand response and wind uncertainty. *Appl. Energy* **2016**, *167*, 270–279. [CrossRef]
84. Zhang, X.; Shahidehpour, M.; Alabdulwahab, A.; Abusorrah, A. Hourly Electricity Demand Response in the Stochastic Day-Ahead Scheduling of Coordinated Electricity and Natural Gas Networks. *IEEE Trans. Power Syst.* **2015**, *31*, 592–601.