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TOWARDS AN INTEGRATED APPROACH FOR MICRO GAS TURBINE FLEET MONITORING, CONTROL, AND DIAGNOSTICS

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ABSTRACT

Real-time engine condition monitoring and fault diagnostics results in reduced operating and maintenance costs and increased component and engine life. Prediction of faults can change the maintenance model of a system from a fixed maintenance interval to a condition based maintenance interval, further decreasing the total cost of ownership of a system. Technologies developed for engine health monitoring and advanced diagnostic capabilities are generally developed for larger gas turbines, and generally focus on a single system; no solutions are publicly available for engine fleets. This paper presents a concept for fleet monitoring finely tuned to the specific needs of micro gas turbines. The proposed framework includes a physics-based model and a data-driven model with machine learning capabilities for predicting system behaviour, combined with a diagnostic tool for anomaly detection and classification. The integrated system will develop advanced diagnostics and condition monitoring for gas turbines with a power output under 100 kW.

INTRODUCTION

Monitoring the condition of a gas turbine and fault diagnostics has been developed to reduce engine life cycle costs, for both operation and maintenance, and to increase safety. This is done by avoiding unscheduled maintenance, detecting partial failures, improving repair schedules and increasing overhaul.

The detection of faults in the engine components is based on deviations in the values of component performance parameters from the baseline values of a "healthy" engine, as determined from measurement data. The main principle lies in the fact that physical hardware faults result in degraded component performance, producing changes in measurable parameters. The detection of these changes allows the isolation of the component whose performance has degraded and the correction of the faulty hardware. A mathematical framework for this process, referred to as Gas Path Analysis (GPA), was provided by Urban (1972). Gas path analysis has been a key tool for engine diagnostics, initially employing a linear model. Extensive research has followed in the field, with Stamatis et al. (1990) introducing a method to take into account the non-linearities in engine behaviour and other studies proposing different techniques to counteract some of the drawbacks of these early models. The models themselves form an integral part of the diagnostic system, and can be physics-based, data-driven, or hybrid (a mixture of the two).

Numerous papers have given an overview of different aspects of the vast literature in the field. As Li (2002) highlights, performance analysis has remained one of the most powerful tools for gas turbine condition monitoring and fault diagnostics. Engine gas-path performance monitoring represents the majority of engine health management related research (Jaw, 2005). An overview of the fundamental theory can be found in Volponi (2014), along with a timeline of past, present, and future trends.

Advances in fleet diagnostics and prognostics

The employment of gas turbine diagnostics has seen a significant increase in research in the field in the last couple of decades, as major engine manufacturers introduced remote monitoring and diagnostic services (Ozgur et al., 2000; Brummel et al., 2005; Therkorn, 2005; Salvaniemi, 2015) and fleetwide monitoring programs were initiated in the power generation industry (Johnson, 2014). Activities ranging from engine monitoring, health tracking, and fault diagnosis to fleet health management, are performed by commercial airlines and power plant operators, original equipment manufacturers

(OEMs) and independent maintenance facilities (Volponi, 2014). Companies and customers value the information that can be provided to assist in troubleshooting or avoid an unplanned event and the effect this has on overall plant efficiency. Information from the fleet is then used to provide a baseline for engine performance and estimate the nominal range of various operating parameters.

Research studies have reflected this, starting to look into engine fleet monitoring and diagnostics, basing their approach on data-driven models. Aircraft fleet monitoring has been addressed by Chu et al. (2010), who constructed a data-driven model for aircraft operation using historical fleet data for anomaly detection. They then presented an approach for population-wide monitoring and detection of performance anomalies, performance shifts, and anomalous units in a fleet of aircraft (Chu et al., 2011). Different approaches were presented by Scheianu (2014) for diagnostics of an industrial gas turbine fleet based on performance monitoring and by Borguet et al. (2015) for data-driven modelling of a fleet of engines, applied to a virtual fleet of generic high bypass ratio turbofans. Machine learning techniques are used more and more for anomaly detection in different applications with promising results. Allegorico et al. (2014) applied logistic regression and artificial neural networks to monitor gas turbine combustors using historical data from a fleet of 150 gas turbines. A deep learning approach using auto-encoders and extreme learning machines was proposed by Yan and Yu (2015) for anomaly detection in combustors.

The ultimate goal in engine condition monitoring and health management is the prediction of the future state of the engine and its components (prognostics). This is linked to diagnostics and judges the impact of a specific fault on the engine or component. It can also take into account the degradation of the components and predict their remaining useful life. Knowledge of when a component might fail allows the shift from reactive to proactive maintenance, significantly reducing response time and costs.

Discussion of prognostics has been on the table since the 2000s; Roemer and Kacprzynski (2000) presented an integrated set of health monitoring, diagnostic, and prognostic technologies for turbomachinery, highlighting the requirements for the prediction of remaining useful life. Many physics-based prognostic models have been presented in the literature, but their application in real systems is quite limited because they are generally complex and computationally expensive, defect-specific, and various parameters need to be determined for each system (Li et al., 2000; Oppenheimer et al., 2002; Qiu et al., 2002). Data-driven models such as exponential smoothing, autoregressive models, and artificial neural networks have been widely employed (Wang, 2004; Orchard, 2005). A simple but effective regression method combined with statistical knowledge for prognostic analysis has been proposed by Li and Nilkitsaranont (2009). An extensive review of prognostic methods and approaches can be found in Heng et al. (2009).

Development of micro gas turbines

In the recent years, work on the field of micro gas turbines (particularly those with low power output levels of 1-100kW) has focused on the development of components and engines with efficiency levels close to those of larger gas turbines. The efficiency levels are limited by small-scale effects, such as low Reynolds numbers which result in high viscous losses, high tip clearances due to manufacturing tolerances, large area-to-volume ratio resulting in high heat losses, and relatively high auxiliary system losses due to the low power output level (Visser et al., 2011). Until recently, overall costs posed a limitation to the development of components, which are crucial for the increase of overall engine efficiency. However, the development of small turbochargers with efficiencies close to those of small gas turbines has allowed the development of micro gas turbines with practical efficiency levels, using off-the-shelf turbocharger parts from the automotive industry. State of the art component isentropic efficiencies for small turbocharger turbomachinery are in the levels of 75% for compressors and 70% for turbines (Visser et al., 2011; 2012) with further room for improvement by optimizing the components for the particular application.

In Visser et al. (2011) a conceptual design of a turbocharger-based microturbine for a heat demand driven micro combined heat and power (CHP) was proposed, with 3kW of electric power, 15kW for heating and hot water, and a target efficiency of 16%. A competitive market for these small CHP units is domestic applications, with the units replacing conventional boilers in larger houses, as well as in small offices, where the output of the unit can cover daily needs. The system has been developed and after four years of field trial will launch commercially in the fall of 2017, exceeding the initial efficiency target and with the aim to increase the efficiency levels to 20% with expected technology development.

FOLLOWING URBAN DEVELOPMENT TRENDS: GAS TURBINES IN SMART CITIES

When looking at energy generation, the share of renewable energy is continually increasing, and the European Union targets a 27% share of renewables along with an improvement of at least 27% in energy efficiency in 2030 compared to projections of future energy consumption and a reduction of greenhouse gas emissions (European Council, 2014), as depicted in Fig. 1.

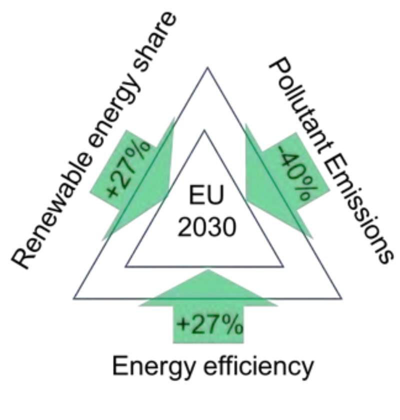

Figure 1: European Union energy policy for 2030

The use of wind and solar power whose generation is intermittent and unpredictable could result in stability issues for the grid and in a time lag between supply and demand of electricity. This results in a significant ramp of demand in the evening hours, graphically represented in what has become known as the “duck curve” (CAISO, 2016). The use of short term batteries at a large scale could provide a solution, however cost is a major limiting factor for production. This creates an opportunity for small combined heat and power (CHP) units, which can provide flexibility of energy production when connected to the grid.

The reduction in energy consumption and the improvements in energy efficiency need to come from all parties involved. However, with buildings accounting for 40% of Europe’s energy consumption (European Commission, 2016), there is a significant margin for improvement. In fact, the role of buildings in the EU policy is expected to expand from energy savings to becoming active elements in future energy systems, allowing their occupants to use, supply and store energy in a more flexible and smarter way. The use of smart electricity meters in the EU (where it is expected to reach 100% implementation by 2020 in many countries, European Commission, 2017) and worldwide allows real-time billing and can help in the reduction of electricity consumption. This needs to be done by engaging the consumers and providing incentives for them to reduce their electricity consumption. A number of studies in Sweden, where substantial practical experience has been gained through the full roll out of smart meters (first country to complete this, in 2009), showed the complexity of customer response to different incentives and highlighted that the potential for energy savings has not been fully exploited (Vassileva and Campillo, 2016). It was noted that a combination of environmental and economic incentives, taking into account the income, educational level and use patterns of the consumers is required in order to maximize energy savings (Vassileva and Campillo, 2014).

The concept for micro-CHP fleet management

A grid based on distributed generation and small combined heat and power plants (micro-CHP) is a good solution to the problem. Small electricity production units can be clustered together and monitored and controlled as a single entity, in a concept referred to as the virtual power plant (VPP). This is defined as the aggregation of load/generation/storage that can act as a single entity in the electricity grid and market (Pandžić et al., 2013; Oates and Melia, 2016). Research has been done on different aspects of a VPP, mostly on improving the visibility, controllability in terms of electricity grid stability, and market functionality i.e. scheduling of distributed energy resources (Saboori et al., 2011; Ghavidel et al. 2016; Nosratabadi et al., 2017). With regards to micro-CHP VPP, research has focused on the technical feasibility, the economic potential, and the institutional environment.

Once the micro-CHPs are connected to the grid (be it on a neighbourhood or larger scale) they can then trade energy in the market according to spot prices and hour by hour price variation for each day. In order for the units to be used for trade in the energy market, a framework for the management of micro CHP is essential. This framework will take care of control and diagnostics of the fleet and will also allow management of the fleet and result in the reduction of overall life cycle costs. The framework will also include a cost

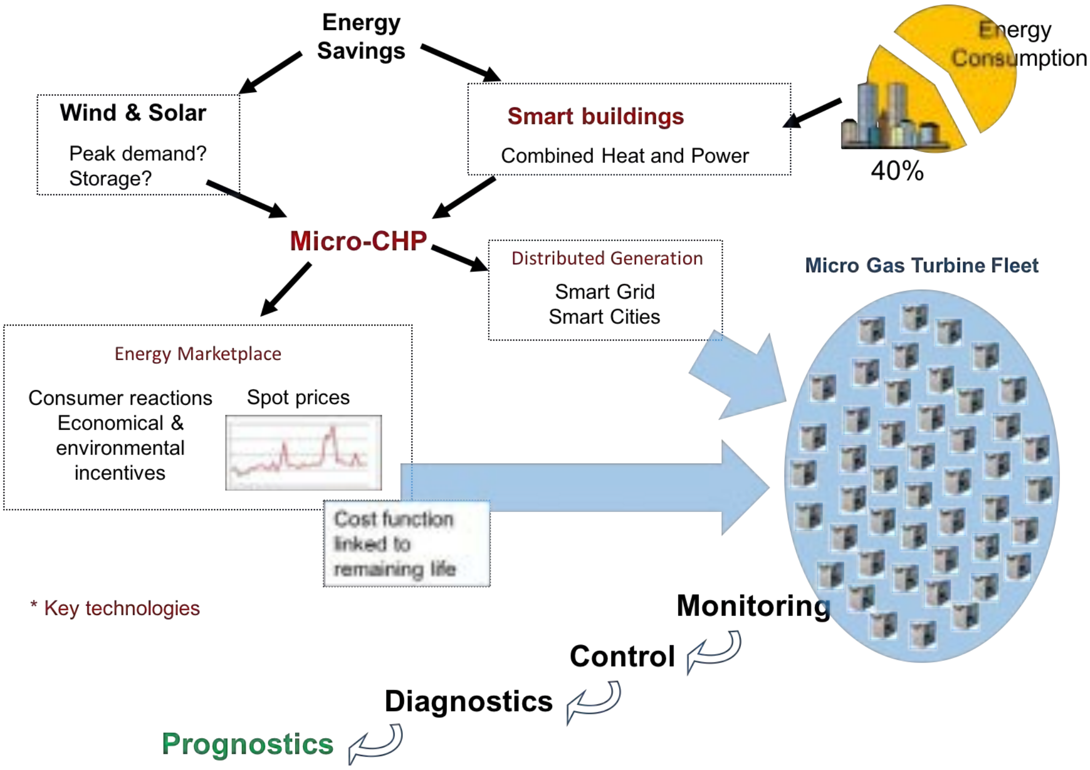

Figure 2: The micro gas turbine fleet concept for distributed generation of combined heat and power (CHP)

function so then the system can make decision on whether it is profitable or not to start the GT to provide electricity to the network. The concept for distributed generation of combined heat and power is schematically depicted in Fig. 2.

Why now?

The advances in instrumentation, communication techniques, and computer technology have allowed the development of advanced monitoring tools for a large range of machines and household devices. The use of monitoring and diagnostics is increasing rapidly across many industries and applications, as sensors are getting smaller, cheaper, smarter, and widespread. Computing is becoming exponentially cheaper and wireless visualization will enable wider deployment. Therefore, the introduction of this technology can now provide significant payback.

The developments in artificial intelligence (AI), with the rise of cloud-based big data platforms and the success of deep learning, have made it easy to collect and analyse large volumes of data (Najafabadi et al, 2015). Thus, a key success factor will be to create a scalable combination of physics-based and data-driven deep AI models for diagnostics, prognostics and control.

The engine of the future, referred to as the intelligent engine, uses engine health management for adaptive control based on the estimated state of health of the engine. This system conducts analysis on-board, allowing the estimation of deterioration, faults, and generating diagnostic and prognostic information to support line maintenance and overhaul logistics (Volponi, 2014). A key aspect of this is the construct of an accurate on-board model that is calibrated to the particular engine being monitored, the digital twin. As the cities get smarter, the energy consumption and overall efficiency and emission targets get stricter, and the grid can support more advanced technologies, the industry needs to be ready.

Challenges of micro gas turbine fleet control

In this scenario, the shift from a large, centralized plant to a fleet of distributed micro-CHP engines raises a number of challenges:

- A big amount of data needs to be collected, stored, and pre-processed taking into account the operating conditions of the machine.
- A single model is not sufficient for fleet diagnostics, as the differences between the engines are not negligible (Zur Nieden and Fiedler, 1999). A model of an average turbine needs to be combined with data-driven regression of every engine in "healthy" conditions. These combined models can be used for comparison with current conditions for anomaly detection and classification.
- The aim for low engine costs limits the number of sensors used, rendering the detection of sensor faults more difficult.
- In the calculation of remaining useful lifetime, the usage profile needs to be taken into account, as the frequent start and stop decrease the remaining life of the engine. This can be done using historical data.

Current OEM fleet monitoring application

During the initial field trial phase, a fleet monitoring application, the Condition Monitoring Diagnostics and Maintenance Tool, was developed at Micro Turbine Technology (MTT). To monitor the CHP systems, every system installed was coupled to a monitoring PC which recorded ~90 parameters every minute or whenever an error occurred. The application shows these parameters nearly real-time. As more systems were put into service, the application was extended to include graphical representations of measurements and corrected data and reporting options to the end users. Maintenance actions and component history and tracking for critical components was also added, as well as diagnostics and preliminary predictive failure detection. The various functions of the application are shown in the following figures. Fig. 3 presents an overview of the fleet of 30 systems, with a map depicting the systems currently installed as well as operational information, the health status and electric output of each system, the total electric power of the fleet, and the share of produced and available power. Fig. 4 shows the measured operational parameters of the CHP system and

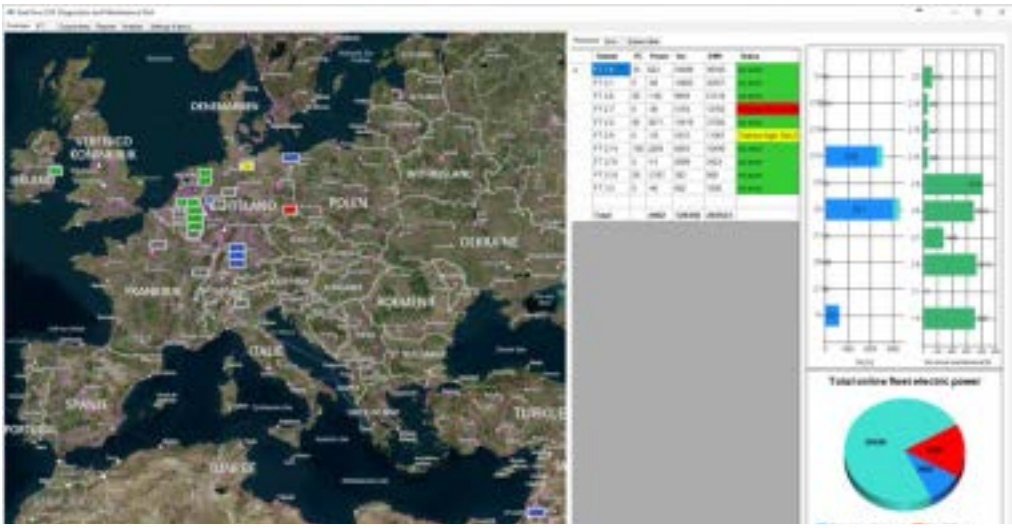

Figure 3: Fleet overview

various installation parameters. Fig. 5 gives a historic overview of key parameters along with their corrected values for both the system as a whole and for some of its subcomponents. This includes the electric and heat power produced, the compressor exit pressure, the fuel compressor speed and the cabinet temperature all plotted against operating time.

FRAMEWORK FOR MICRO GAS TURBINE FLEET MONITORING AND DIAGNOSTICS

As the production of power is shifted toward distributed micro-CHP units and the number of systems in a fleet increase from a few dozen to hundreds or thousands, the approach for monitoring and diagnostics needs to be extended to a wider framework that addresses the challenges discussed in the previous section. To limit the maintenance cost, an effective early detection of faults and condition-based maintenance have to be implemented.

The proposed framework features a multi-level approach. With thousands of machines in the fleet and 90 parameters monitored every minute, an automated system is essential for fleet monitoring and anomaly detection. When an anomaly is detected, the particular machine is isolated and a three-level anomaly classification algorithm (ACA) is run on the engine. On the first level, data from all micro gas turbines is collected and processed to filter noise and correct the measurements with the ambient and operating conditions. Machines with similar operating conditions are compared to each other and to a model of an average turbine to detect outliers (measured values that are far from the expected values after taking into account manufacture differences and uncertainties). When the outliers exceed a pre-determined threshold, the anomaly is detected and the machine performance is analysed.

The second level includes a sensor fault detection system to determine if the anomaly is caused by a faulty sensor rather than an actual failure or degradation in the turbomachinery

Figure 4: Current system state

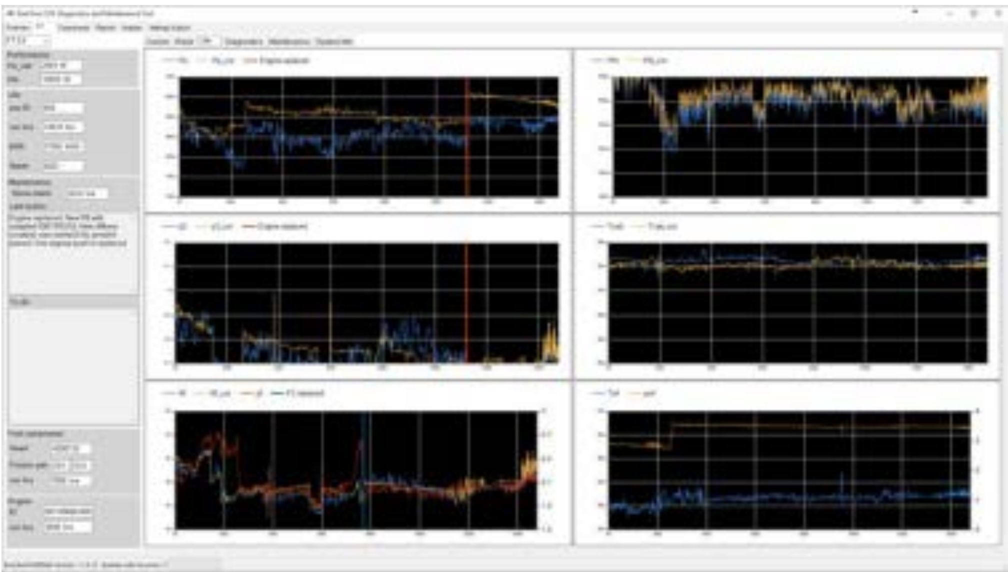

Figure 5: Historic overview of key parameters and corrected values

component. For this purpose, the measurements can be compared to a digital twin of the turbine, based on a physics-based model and tuned with data from the engine using a regression method. If a sensor fault is excluded, the ACA looks for a fault in a turbomachinery component. The ACA uses the digital twin to generate fault signatures, which are then compared to the actual measurements and the residuals between the measurement and the signature are minimized.

The next level is the prognostic system. If the failure is severe, a maintenance time is recommended. When gradual degradation is detected due to normal wear and tear, a life prediction model will calculate the estimated remaining useful lifetime of the machine, based on the historical operating profiles. The proposed framework is presented in Fig. 6.

Once the framework is in place, a cost function can be added to the life prediction model, which can communicate with the grid and receive real-time information on the price of electricity and thermal energy. A smart system will then evaluate the optimal operating and maintenance strategies to minimize the cost function and maximize the economic return for the user.

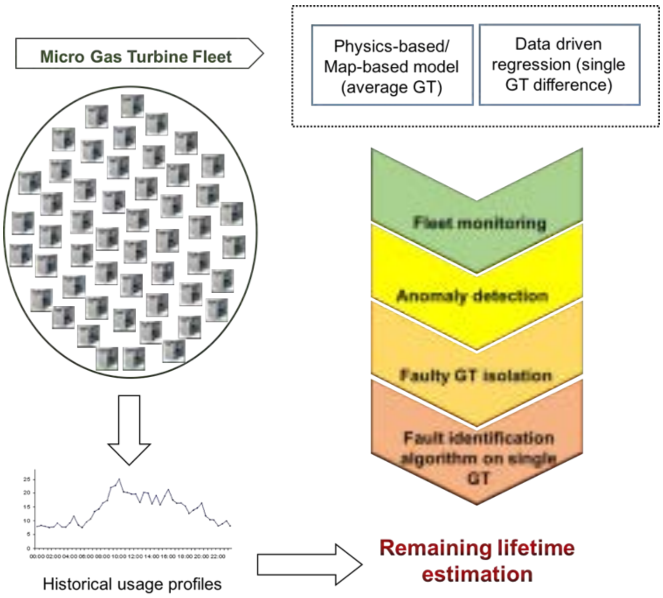

Figure 6: Framework for micro gas turbine fleet monitoring and diagnostics

CONCLUSIONS

As technology plays a bigger role in everyday life, with smart devices connected to smart grids, and automation is governing the operation of numerous small and large devices and machines, real-time monitoring and control is becoming more widespread.

The advances in turbocharger technology have allowed the development of micro gas turbines with power output below 10kW electric that are cost-effective and can be used for micro CHP systems in domestic applications. Furthermore, advances in computing power and sensor technology with lower costs propel the development of more advanced diagnostics and health prediction functions and yield new possibilities and applications for the monitoring of gas turbines. The technology has reached a level of maturity that allows the implementation of diagnostic functions in small devices, such as boilers and combined heat and power plants using micro gas turbines.

This paper presented an integrated framework for monitoring, control, and diagnostics of a fleet of micro gas turbines. Challenges for fleetwide monitoring include the processing of a large amount of data and the need for specific models for each engine. Specific challenges for the micro gas turbine fleet are the limited number of sensors available, as the development a competitive system requires a small unit cost, and the need to take into account the usage profile of the engine in order to accurately predict its remaining life.

The framework will allow the connection of the gas turbine to the grid and the energy marketplace and provide the possibility to sell energy to the grid when needed. For this functionality, a cost function will be included in the system, which will communicate with the market and determine the more remunerative operating strategy taking into account the possible lifetime decrease due to high fired temperature operations or quick load cycles.

NOMENCLATURE

ACA	Anomaly Classification Algorithm
AI	Arificial Intelligence
CHP	Combined Heat and Power
EU	European Union
GPA	Gas Path Analysis
MTT	Micro Turbine Technology
OEM	Original Equipment Manufacturer
VPP	Virtual Power Plant

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