Progress in Modeling and Control of Gas Turbine Power Generation Systems: A Survey

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Abstract: This paper reviews the modeling techniques and control strategies applied to gas turbine power generation plants. Recent modeling philosophies are discussed and the state-of-the-art feasible strategies for control are shown. Research conducted in the field of modeling, simulation, and control of gas turbine power plants has led to notable advancements in gas turbines' operation and energy efficiency. Tracking recent achievements and trends that have been made is essential for further development and future research. A comprehensive survey is presented here that covers the outdated attempts toward the up-to-date techniques with emphasis on different issues and turbines' characteristics. Critical review of the various published methodologies is very useful in showing the importance of this research area in practical and technical terms. The different modeling approaches are classified and each category is individually investigated by reviewing a considerable number of research articles. Then, the main features of each category or approach is reported. The modern multi-variable control strategies that have been published for gas turbines are also reviewed. Moreover, future trends are proposed as recommendations for planned research.

Keywords: gas turbine; power plant; mathematical modeling; intelligent modeling; system identification; predictive control; intelligent control

1. Introduction

Modeling and control of gas turbine (GT) power generation systems are very important and are interrelated disciplines to study and improve the GT performance and efficiency. Understanding GT dynamics before actual installation or existing GT units cannot be achieved without sufficiently accurate models. GTs have occupied a privileged position among other power generation technologies for many reasons, including: high reliability; higher efficiency, especially when integrated with combined cycle; flexible operation; and regular availability [1,2]. The advances in GT operation and efficiency have occurred either from progress in GT control system philosophies [3] or introducing new designs [4]. GTs can be found in applications including engines used in aircraft and gas turbines used in power generation plants [5,6]. Due to the differences in the practical objectives between aircraft gas turbines and power generation gas turbines, the review presented here is dedicated to gas turbine power generation plants (GTPGP) used in power systems, whether they are studied on their own open cycle or as a part integrated to steam cycle in combined cycle gas turbine (CCGT) power plants. Therefore, for organizational and directive research reasons, the models for aircraft gas turbines are not included in this survey. Throughout our reading of the published research in this research area, the survey papers were found to be too general, and more specific review is needed [7–10]. The reviews in [7,8] summarized the GT modeling up to 2008 and 2011, respectively, with rather short explanations, whereas the survey in [9] is a general survey of thermal power plant simulations. Recent

reviews on gas turbines diagnostics have been published in [10,11], however, those surveys have reported the methods of GT diagnosis and do not focus on modeling-based control theory and dynamic performance studies. The survey in this paper rather focuses on the models-based control and dynamic performance studies for gas turbine generation units. There is an urgent demand to reorganize the most recent and state-of-the-art methods of developments in GTPGP modeling and control, classify them properly, and discuss how they are cognitively connected with what had been previously published. The contribution of this paper is then to provide a more updated and a comprehensive survey about dynamical modeling of GTPGP from control point of view and the feasible methods of control that can be integrated to the GT unit with compliance of operational restrictions. The survey is beneficial for reporting the state-of-the-art techniques and attempting to extract future trends in the field. The survey is organized as follows: The modeling part has been divided according to the modeling philosophy and compared against each other. Moreover, the study outlines the feasible control strategies of gas turbine generation systems and discusses the future opportunities in the field. The survey offered in this paper shall be confined to GTs used in power generation or GTPGP for two main reasons: firstly, to understand and justify the dramatic growth of GTs in electricity sector as a power system resource and its positive influences on the power grid performance, such as grid stability and continuity of service; and secondly, the survey will simplify the way to investigate more feasible and safe operation strategies for compliance of grid codes specified by the system authority in different countries, which is a very specialized requirement in power plant engineering. The rest of the paper is organized as follows. Section 2 shows the fundamentals of gas turbine power generation systems and some principles of their modeling. The survey of dynamic modeling of gas turbines from control point of view is presented in Section 3. Section 4 reveals the survey of the different control strategies of the relevant validated control systems of gas turbine power plants. Section 5 discusses the possible future trends in the field, and finally Section 6 provides the conclusion of the paper.

2. An Overview on Gas Turbines Power Plants and the Purposes of Their Dynamical Modeling

Gas turbines are widely used for propulsion and power production applications [12–14]. Consequently, for all industrial applications of GTs, modeling procedures and control methodologies are widely reported in the literature. Proper operation strategies are the key objectives to be fulfilled by process simulation and control. The essential parts of a typical gas turbine are shown in Figure 1, which are a compressor, a combustor or combustion chamber, and the turbine. Figure 2 shows the entropy–temperature (T–S) diagram of a typical GT unit. The air that is necessary for firing is fed by the compressor (control volume 1–2). In the firing chamber, the fuel/air mixture is combusted (control volume 2–3). Ideally, the control volume 1–2 contains isentropic process whereas control volume 2–3 is an isobaric process. The burnt gases are expanded in the turbine as an isentropic process (control volume 3–4) which produces the required mechanical work which is sufficient to drive the rotor of the synchronous generator (SG). Finally, in (1–4), the heat is rejected with fixed pressure. Gas turbine usually exists as a part of combined cycle unit in which the gas exhausted from the gas turbine is harnessed by the heat recovery steam generator (HRSG) to supply a high energy steam to the steam turbine (ST). The electrical power is delivered by the synchronous generator.

There are many goals and objectives for the modeling of GT or CCGT, including:

1. Simulators for training purposes [15–18].
2. Conditions monitoring and fault diagnosis [11,19–21].
3. Upgrading the performance by control system analysis [3,22–40].
4. Stability Studies (large signal and small signal stabilities) [22–26].

Apart from these modeling objectives, and to grasp the trends of the modeling literature of GTs, the modeling survey can be classified in a better and clearer manner as follows:

1. Physical models based on the physical laws and parameters identification by data sets.
2. Empirical models with predefined structure, which are based on operational data sets.

3.　　Simplified mathematical models which are mostly transfer functions derived from system physics and identified to fit the plant manufacturer responses.

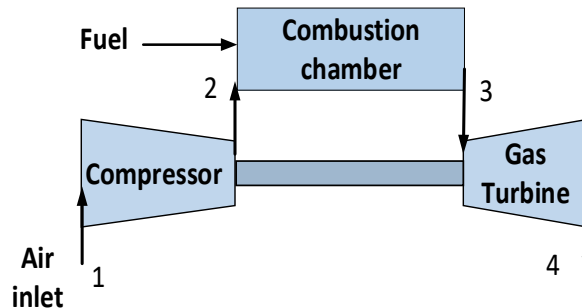The next section reveals the significant differences between the models within each sorting.

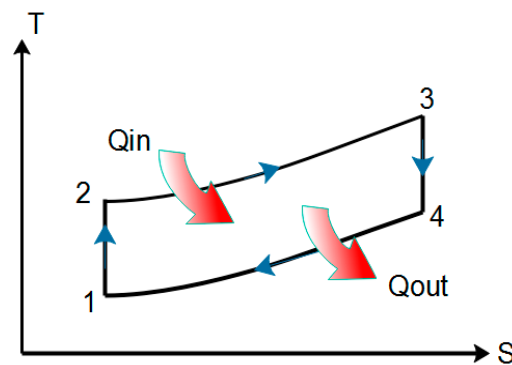**Figure 1.** Main components of gas turbine unit.

Figure 2. Temperature–Entropy (or T–S) diagram.

3. Modeling Approaches for Gas Turbine Power Generation Plants

In this section, the major gas turbine modeling methods will be reviewed. Our review starts with old techniques and model versions up to recent developments and achievements by 2020. It is perhaps necessary to classify the reported models as in the previous section to deduce the significant differences between the models within the same classification and also to compare one classification to another in terms of accuracy and computation capability requirements. This qualitative comparison provides meaningful survey where the suitability of each category for a specific application will be realized.

3.1. Physical Modeling

Physical principles modeling, and sometimes referred to as first principles modeling, is the most sophisticated method of modeling dynamic systems; it provides physical process interpretation in the form of mathematical equations, algebraic and differential equations, to describe the system behavior. For GTPGP, the principles of mass and energy conservation are commonly used. Energy is converted into many forms in GTPGP before it is released as electricity to the grid. Mathematically speaking, it can be written as

$$\frac{dE_{sys}}{dt} = \dot{E}_{in} - \dot{E}_{out} \tag{1}$$

The concept of energy conservation is explained in words, which states that the net energy transfer rate by heat, work and mass equals to the rate of change of the energy inside a control volume or a system or subsystem, which is the rate of change in the internal, kinetic, and potential energies inside the control volume. However, in case of steady-flow process, the energy balance for the cycle can be given as:

$$\dot{E}_{in} = \dot{E}_{out} \tag{2}$$

Similarly, the mass balance equation is described as:

$$\frac{dm_{sys}}{dt} = \dot{m}_{in} - \dot{m}_{out} \tag{3}$$

Equations (1)–(3) can be found in all textbooks of thermodynamics. GTPGP simulations based on physical principles are dated back to several decades using digital or even analog computers [23,24]. Nevertheless, it has been still in use up to recent research and development with the same principles, but with different assumptions, different parameters' identification techniques, and different purposes [25–28]. However, there has been a systematic procedure used in all modeling studies reported in this survey that starts from derivation of the equations that govern the system physics, identify its parameters, up to computer verified simulations. These steps are applicable for all cited articles. The processes are described in the flow diagram shown in Figure 3, in which the upper dashed red box contains the mathematical derivation phase of the research and the lower dashed red rectangular embeds the computer implementation and model verification.
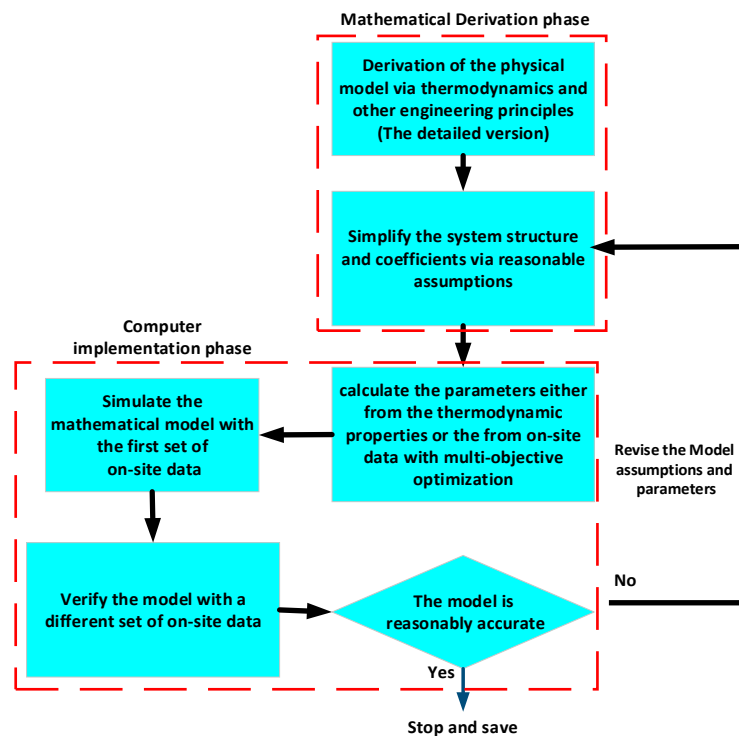
Figure 3. The general systematic approach to develop physical models or mathematical models that are rooted from system physics.

Some basic principles for modeling are introduced under commonly used assumptions. When changes in kinetic and potential energies are ignored, the aforementioned energy balance equation, for steady flow process, and by referring to Figures 1 and 2, can be alternatively interpreted by the following equations that depict the compressor and turbine processes [22,29,41–43].

$$(q_{in} - q_{out}) + (w_{in} - w_{out}) = h_{ext} - h_{int} \tag{4}$$

$$q_{in} = h_3 - h_2 = c_p(T_3 - T_2) \tag{5}$$

$$q_{out} = h_4 - h_1 = c_p(T_4 - T_1) \tag{6}$$

$$\dot{Q}_{in} = \dot{m}_{FU}c_p(T_3 - T_2) \tag{7}$$

$$\dot{Q}_{out} = \dot{m}_{FU}c_p(T_4 - T_1) \tag{8}$$

$$\frac{T_2}{T_1} = \left(\frac{p_2}{p_1}\right)^{\frac{k-1}{k}} \tag{9}$$

$$\frac{T_3}{T_4} = \left(\frac{p_3}{p_4}\right)^{\frac{k-1}{k}} \tag{10}$$

$$\eta_{th} = \frac{\dot{W}_{net}}{\dot{Q}_{in}} = 1 - \frac{\dot{Q}_{out}}{\dot{Q}_{in}} \tag{11}$$

$$\dot{W}_{net} = \dot{Q}_{in} - \dot{Q}_{out} \tag{12}$$

where q_{in} and q_{out} are the input and output heat transfer, respectively. w_{in} and w_{out} are the works done by the compressor and the turbine, respectively. p is the pressure h is the enthalpy and T is the temperature of the relevant system point determined by the subscript and by referring to Figure 2. $\dot{m}_{FU}$ is the gas flow rate, k is the specific heat ratio and $\dot{W}_{net}$ is net work rate, which results from the difference between heat transfer rates $\dot{Q}_{in}$ and $\dot{Q}_{out}$. The turbine and compressor are ideally described through Equations (4)–(12). The combustion chamber is also governed by the first law of thermodynamics. The combustion can also be related directly to the changes in the control valve and pilot valve by second order transfer function that visualize the physical combined effect of these actuators' adjustment on the combustion stability. The valve actuators are usually modeled by first order lag transfer function that represents the time constant for the actuators followed by rate limiter, if known by the plant manufacturer. They are direct inputs to the plant, named in Figure 4.
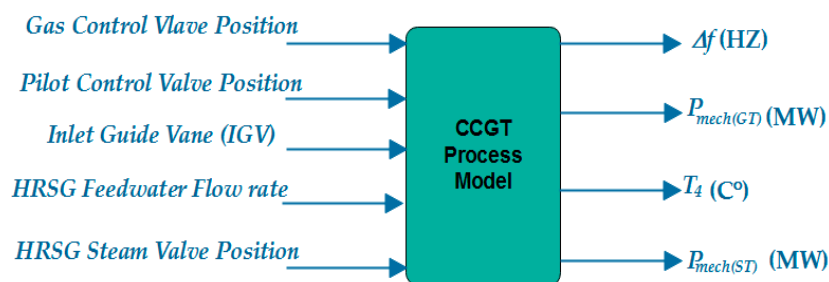
Figure 4. Typical process inputs–outputs for the combined cycle gas turbine (CCGT) process model.

It is more realistic to integrate the GT cycle model to a synchronous generator model. In that case, a care must be taken for units convenient. Most synchronous generator models have normalized per-unit (pu) parameters. In such cases the net work rate or power $\dot{W}_{net}$ is multiplied by unknown parameters (say K_1) to get the normalized mechanical input power. By modeling the GT–generator unit together, some important interactions with the grid, such as undefrequency situation, that can be simulated and its effect on the mechanical stresses on the GT can be studied. The following synchronous generator model is suggested [44]:

$$\dot{\delta} = \Delta\omega \tag{13}$$

$$J\Delta\dot{\omega} = \Gamma_a = \Gamma_{mech} - \Gamma_e - D\cdot\Delta\omega \tag{14}$$

$$\dot{e}'_q = \frac{1}{t'_{do}}(E_{FD} - e'_q - (x_d - x'_d)\cdot i_d) \tag{15}$$

$$\Gamma_{mech}(p.u) \approx P_{mech(GT)}(p.u) \tag{16}$$

$$\Gamma_e(p.u) \approx P_e(p.u) \approx \frac{V}{x'_d}e'_q\cdot\sin\delta + \frac{V^2}{2}\left(\frac{1}{x_q} - \frac{1}{x_d}\right)\sin 2\delta \tag{17}$$

$$i_d = \frac{e_q' - V \cos \delta}{x_d'} \tag{18}$$

where Γ_{mech} and Γ_e are the mechanical and electro-magnetic torques respectively. We have given this symbol to the torque to give it distinct meaning from the temperature. δ is the voltage angle and $\Delta\omega$ is the frequency deviation. E_{FD} is the equivalent coil Electromotive force (EMF) and it is reasonable to treat it as overexcited and constant, which is likely. e_q' is the generator internal voltage and x_d and x_q are the generator direct and quadrature reactances, respectively. i_d is the direct current in the stator, V is the terminal voltage and finally $P_{mech(GT)}$ and P_e are the generator mechanical and electrical powers, respectively.

If the GT is a part of CCGT unit, the HRSG model should be considered, especially for control and energy efficiency purposes. The modeling principles of HRSG are the same that of heat exchanger, whether it is subcritical or supercritical. The features of the HRSG are described by the following two equations of the heat exchanger model in [45]:

$$\dot{p}_{hx} = \frac{\dot{Q}_{hx} + \dot{m}_i \left(h_i - h_{hx} - \frac{\rho_{hx}\frac{\partial h_{hx}}{\partial T_{hx}}\big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}}\big|_p}\right) - \dot{m}_o \left(h_o - h_{hx} - \frac{\rho_{hx}\frac{\partial h_{hx}}{\partial T_{hx}}\big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}}\big|_p}\right)}{V_{hx}\left(\rho_{hx}\frac{\partial h_{hx}}{\partial p_{hx}}\big|_T - \frac{\rho_{hx}\frac{\partial \rho_{hx}}{\partial p_{hx}}\big|_T \cdot \frac{\partial h_{hx}}{\partial T_{hx}}\big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}}\big|_p} - 1\right)}$$

where subscript *hx* means heat exchanger. ρ is the density and V is the volume. The pressure state equation can be further reduced to

$$\dot{p}_{hx} = \frac{\dot{Q}_{hx} + I_{i2}\dot{m}_i - I_{o2}\dot{m}_o}{C_{hx}}$$

where C_{hx}, $I_i = \left(h_i - h_{hx} - \frac{\rho_{hx}\frac{\partial h_{hx}}{\partial T_{hx}}\big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}}\big|_p}\right)$ and $I_o = \left(h_o - h_{hx} - \frac{\rho_{hx}\frac{\partial h_{hx}}{\partial T_{hx}}\big|_p}{\frac{\partial \rho_{hx}}{\partial T_{hx}}\big|_p}\right)$ are unknown parameters, which can be considered as fixed unknown parameter to be identified by optimization algorithm, or distributed parameter computed by look-up tables. The final format of nonlinear state equation for the pressure inside the HRSG can written as

$$\dot{p}_{hx} = \frac{\dot{Q}_{hx} + I_{i2}\sqrt{p_{inlet} - p_{xh}} - I_{o2}\frac{K_3 p_{hx} u_{SCV}}{\sqrt{T_{hx}}}}{C_{hx}} \tag{19}$$

where K_3 is an unknown parameter to be identified and u_{SCV} is the main steam valve position, which appears as direct input to the plant in Figure 4. The temperature state equation can be given as [45]:

$$\dot{T}_{hx} = A\left(\dot{m}_i - \dot{m}_o\right) - B.\dot{p}_{hx} \tag{20}$$

where

$$A = \frac{1}{V_{hx}\frac{\partial \rho_{hx}}{\partial T_{hx}}\big|_p}$$

$$B = \frac{\frac{\partial \rho_{hx}}{\partial p_{hx}}\big|_T}{\frac{\partial \rho_{hx}}{\partial T_{hx}}\big|_p}$$

The steam turbine power is the represented by the steam flow rate multiplied by the enthalpy drop:

$$P_{mech(ST)} = \Delta h \dot{m}_o \tag{21}$$

To track the detailed derivation of the heat exchanger model that can be considered as the same as the HRSG model, refer to [45]. The model contains many dynamic states; it is preferred to represent the whole model as components to know the physical interpretation of these equation. The model equations from (4) to (20) is in nonlinear dynamic states format and embedded with some algebraic equations. The heat transfer to the HRSG can be coupled to the rest of model components by any appropriate relationship between the exhaust temperature and the heat transfer rate (convection or combined heat transfer of convection and conduction) or by direct gain relationship. The GT exhaust temperature is normally governed by conventional controller that modulates the turbine exhaust temperature in-line with the effective temperature set-point. This controller can be assumed to be PI controller with unknown parameters included in the model. This is because the modeling and identification procedures are done on the closed loop system with the classical controllers embedded to the system. The typical inputs and outputs of CCGT process model are shown in Figure 4, which comply with the aforementioned mathematical and wordy descriptions. The choice of inputs and outputs is arbitrary and depends on the study objectives. We normally add the inlet guide vane (IGV) of the compressor as additional actuating input for better compression ratio, and it can be related to equation (9) via basic actuator model. The usual outputs are the power, temperature and frequency to gain the duel objectives of frequency regulations and higher energy efficiency.

The inputs vector is $[u_{GCV}\ u_{PILOT}\ IGV\ u_{SCV}\ u_{FW}]$ and the output vector is $[\Delta f\ P_{mech(GT)}\ T_4\ P_{mech(ST)}]$. The operational constraints of the inputs vary from one CCGT to another, which includes the valve movements and the rates of those movements. An overview about how to create a model for GTPGP has been given.

The literature review has given many strong candidates of models with the common aforementioned strategy of modeling, and it is not the target of this paper to repeat all equations and derivations here. Therefore, an informative discussion will be adequate for each individual study to describe the scientific contribution of each one selected with some remarks on the relevant results. The survey covers open cycle and combined cycle gas turbines' generation systems. It might be unfair, or even unnecessary, to compare the models' performance quantitatively with emphasis only, for instance, on the numeric level of the accuracy, because that depends on factors other than the model structure, such as the field data and the level of variations in that set of data. Overall comparison goes beyond that, especially when it is known that all published models have been extensively verified by such a way or another, and thus they are sufficiently accurate from an engineering expertise perspective. It is also important to mention that the physical modeling concepts have remained unchanged for many years, so the novelty that has been noticed recently is found to be in the method of parameters identification, as well as some successful assumptions for the sake of simplicity and feasible applications of new control strategies.

For example, Schobeiri et al. [25] have developed what they have called "GETRAN", which is a generic computer code for simulating the gas turbine dynamic behavior. The modularly structured simulation code has been developed and the nonlinear behavior of the GT has been simulated through solving several partial differential equations that govern the dynamics of the individual subsystems or control volumes. Every component has been described via the partial differential equations that have been based on the thermo-fluid mechanics' laws of conservation. Some parameters have been determined from steady state conditions and other correlation means. The GT power generation model has been validated by 30 MW load rejection and adverse to 8 MW load application after 6 s of the load rejection. There was a close agreement, but with an unavoidable deviation between the load schedule and the shaft response that has been reflected eventually on the shaft speed response. However, the simulator is capable of accurately following the main variation trends of the real system. The model was created as simulation library that contains graphical symbols representing each process, these graphical symbols include components such as compressor, turbine and so on [25].

Hussien et al. [26] derived a simplified version of single-shaft gas turbine physical model. The model has been rooted from thermodynamic principles of mass and energy conservation, with

some simplifying assumptions, to have lumped parameter model. Mainly, the specific heat ratio has been chosen through observations to match the plant manufacturer data to enhance the derived model capability to simulate the real system responses. The results of the simplified model have been promising compared with the manufacturer's model for changes of 2 MW, 4 MW, and 5.8 MW.

Recently, Chaibakhsh et al. [27] have developed an analytical model of heavy-duty GTs. Mass and energy conservation principles have been used mainly to build the model. Some other semi-empirical correlations that are newly introduced to the system to reflect the dynamic behavior of the compressor pressure ratio (CPR) and other major dynamical variables. The model parameters of the model have been identified using constrained nonlinear optimization technique, which is the genetic algorithm (GA). Detailed model accuracy has been confirmed through wide range of simulations for a 72 hour time window and power variations from 145 MW to 160 MW.

More recently, Mohamed et al. [22] have developed a simplified physical model for a gas turbine generation system as a part of comparative study with other approaches of modeling. The model equations are based on thermodynamic principles and have subjected to some assumptions for the sake of simple structure. The GT model has been linked to the synchronous generator model in the q–d frame that facilitates the stability studies of the whole unit. The fuel flow has been presented as a combination between the pilot valve and control valve actions with some fixed parameters. The unit model has been implemented in the MATLAB/SIMULINK environment and the model parameters, such as specific heats, unit convenient parameters, and generator coefficients, have been identified via GA technique to match a gas turbine in a CCGT unit. Accurate results have been depicted that show agreement between the physical model and real data trends for the responses of power, exhausted temperature and frequency deviation. However, the maximum normalized root mean squared error (NRMSE) for the simulator responses is 13.7% for power response that varies from 120 MW to 240 MW while other percentage errors have been relatively very small. It has been proved that physics-based models preserve their physical insight more than other data-driven models despite the fact that it is less accurate in identification phase of the simulation. The suitability of the various models for control system upgrades has been justified.

MATLAB hasn't been the only choice of computer implementation. El Hefni et al. [28,29] have modelled GT and CCGT using an object-oriented modeling (OMM) approach in the *Modelica* simulation environment. The simulation package contains a group of sub-libraries, each sub-library has a number of icons that represents the individual components of the system (e.g. the compressor, the turbine, etc.). Some static and dynamic results have been reported, such as generated power reduction and GT trip [28]. The results of power reduction scenario have been consistent. In the GT trip scenario, the evaporator recirculation flows haven't quite settled down to the zero level as expected and there are no clear reasons that have been given to explain this. However, two reasons may be suggested here to explain that one reason may be that the governing equations of the GT in shut-down mode are slightly different from normal mode grid-connected operations for power production. Another possible reason states that the thermal inertia goes beyond the simulation time window and if the time window is extended, then the evaporation recirculation flows settlement can be observed.

Casella et al. [30] have used Thermo-Power Library of *Modelica* for simulation of startup process for CCGT with GT unit capacity of 250 MW and their associated controllers. The main operational objective of that research was to obtain faster startup process of the CCGT, which is very beneficial for improvement of the quality of power or electricity market.

Reddy et al. [31] have shown different shutdown simulation and thermal via 2-D axisymmetric fully featured turbine model and detailed computational fluid dynamics (CFD) studies. In comparison with experimental results, the model has been promising of prediction of GT shutdown behavior of the GT. Prediction of shutdown consequences is very useful to enhance the operator decisions before actual emergency shutdown or intended shutdown.

J. H. Kim et al. [32] have used one-dimensional unsteady conservation laws to develop a physical model for 150 MW GT with very accurate results to simulate the GT power behavior from 150 MW to

120 MW. However, some unavoidable mismatches are clearly noticed in responses of the exhausted temperature that changed abruptly from 600 °C to 620 °C and the speed or frequency deviation response.

The aforementioned work in [32] has been extended in [33] for the whole combined cycle unit. Shin et al. [33] reported an analysis of the dynamic characteristic of CCGT. The transient form of the energy and mass conservations have been used to construct the model. Some coefficients have been determined using correlation equations and others determined from the thermodynamic properties for the HRSG. Rapid increase, rapid decrease, and periodic oscillation of the GT load were simulated and it was found that the thermal inertia of the steam cycle is much larger than GT cycle.

Oyedepo et al. [34] have presented a thermodynamic model for a 33.5 MW gas turbine with focus on the evaporator cooler. The component-wise modeling was conducted using the mass and energy conservation laws and the coefficients were evaluated using some polynomial equations. Some parameters, such as specific heat capacity of air and combustion product have been considered to be a function of the temperature and embedded to the model via polynomial equation in the temperature that is valid within specific temperature range. It has been proved that when the evaporation cooler is employed to the system, it improves the overall GT thermal efficiency. However, this model embeds high nonlinearity in the temperature variable and it may not be preferred for control system synthesis over other reported candidate models. Nevertheless, the significance of the model brings out the possible study of evaporation cooler influences on GT efficiency.

T. S. Kim et al. [35] have modeled the startup process of CCGT using thermodynamic principles, and the various parameters are either determined using empirical equations or from the properties of exhausted gas and water in the CCGT. Since this model is dedicated to the startup process, it can be more beneficial for conditions monitoring to assure the readiness of the plant for grid integration.

Mohammadian et al. [36] have developed a contemporary simulator for thr GT startup process. The advances that have been added to this modernistic research is that CFD simulation tool have been used to produce the GT characteristic curves and the air-cooling has been modeled by novel approach that takes into account the effect of mainstream chocking position on the turbine performance. Moreover, some blocks and look-up tables have been added to simulate load-following mode. Some model parameters have been found using thermodynamic or thermos-physical properties of the system, and others, like convection heat transfer coefficient, have been adopted from previous research.

Yee et al. [37] have presented a validated model of GT based on thermodynamic relationships. Some parameters are calculated by the temperature differences in the power turbine and the compressor as have been given by the data in steady state to represent the highly nonlinear changes in gas properties, whereas heat capacity ratio has been regarded as constant. Simulation results have been validated for small and large disturbances for performance comparison of the major types of GTs, which are the twin shaft and the single shaft GTs.

Rashid et al. [38] have reported dynamic simulations of hybrid GT–solar power plant with its associated controls for techno-economic analysis of the hybrid unit. The solar component is a concentrated solar power (CSP) structure. The model is based on thermodynamic principles and the model coefficients have been calculated via thermodynamic and heat transfer empirical relations. The work has been intended to show the effectiveness of hybrid power plants with energy storage for cleaner power production, and in that sense, the power simulations generated have been depicted as varied from 80 MW to 140 MW with distinct contributions as figure legends for the gas and solar power.

Other simplified versions have been shown for analogues objectives of simulation and optimization purposes [39,40]. In summary, it is found that general principles for model formulation are very systematic and can be readily derived with the basic background of thermodynamics and mathematical analysis. The differences have been in the method of parameter identification, the simulation tool, the model size, and the flexibility to upgrade the control systems. Table 1 summarizes this diversity with reciting the relevant references that have been used to write this sub-review with some relevant remarks.

Table 1. Summary of gas turbine (GT) physical modeling reviewed references.

Parameters Determinations	Philosophy: Detailed/Simplified		Feasibility for Control System Design/Expansion	Operation Mode		
Parameters identified by Multi–Objectives Optimization [22,27].	Detailed	Simplified	[22–42]	Start-up [30,35,36]	Shutdown or trip-out [28,31]	Load following [22–29,32–34,36–40]
	[23,25,27,30,32,35–38,41,42]	[22,26,39,40]				
Parameters calculated from Thermodynamic Properties in gas and water and /or Thermo-Physical Properties in the system [23–26,28–42].	**Remark**: The detailed models are generally more accurate than simplified models from wide observation of the results. However, the computation demands for the simplified ones are less.		**Remark**: The control systems are easier to implement for the simplified models. This is mainly due to the large computation burden behind the simulation of detailed models that embed high nonlinearity, such as CFD models. However, proper design of control systems result in successful application on both, detailed and simplified.	**Remark**: some models can be applicable to simulate two modes of operation. For instance, reference [28] presents the results for load reduction and GT trip-out. Then it can be regarded as multi-process GT model.		

3.2. Empirical (Black-Box and Grey-Box) Modeling

Empirical models depend heavily on system data and the researcher has some choices to construct the model and fit it directly to the field data. Unlike first principles modeling, there are no mathematical derivations rooted in the physical laws involved in developing empirical models and all procedures are done in the computer implementation stage. Therefore, the selected data sets are imported to the computer, the pre-defined model structure is chosen, and the identification or training algorithm is executed. The next subsection reviews the main achievements in system identification of gas turbine generation units.

3.2.1. System Identification Techniques

Again, it is important to emphasize that the overall review and this sub-review support the dynamic modeling of gas turbine power generation systems, not for aircraft gas turbines. This sub-review classifies the reported models according to the models' structure and the identification algorithms. The general system identification (SI) loop is shown in Figure 5. Generally, the theory and research of system identification began in mid-60s on state variables and transfer function formats [46–48]. Among numerous papers that have reported system identification applications in industrial systems, the SI models for GTPGP are reported in this survey. Many articles have been published on linear and nonlinear identification of gas turbines.
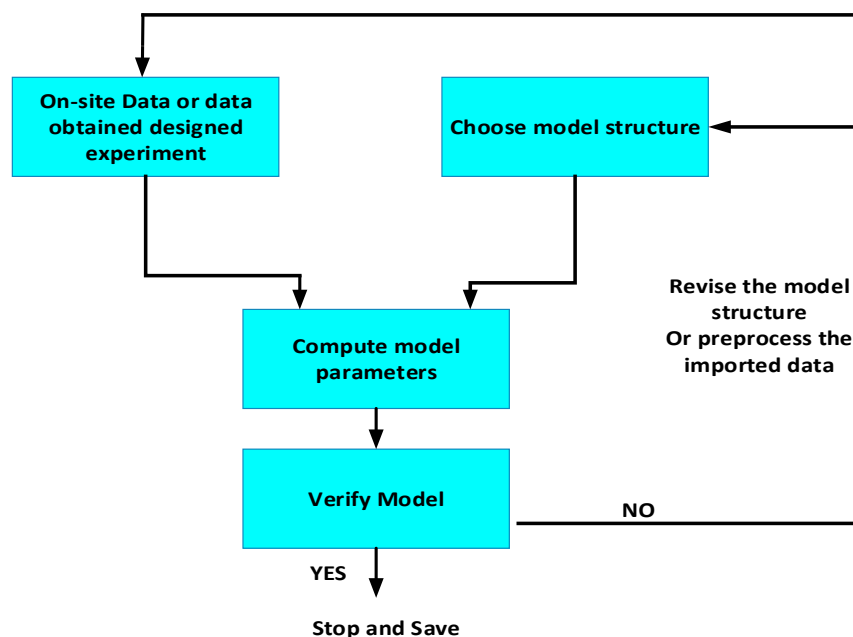

Figure 5. The empirical modeling procedure.

Basso et al. [49] have reported results that prove the capability of the nonlinear autoregressive (NARX) for GTPGP made by General Electric–Nuovo Pignone. The Gram–Schmidt procedure has been used to identify the GT model in isolated and grid-connected modes. The power plant has been divided into three main subsystems: the gas preparation system, the turbine, and the load. Isolated and non-isolated operations have been considered. The model parameters have been identified using the least squares method (LSM) and the NARX model has been extensively validated with real observation of the power output and correlations or residuals tests. The NARX model responses and relative error variations have indicated the nonlinear model superiority over the linear autoregressive (ARX) model for power variations from 3 MW up to 10 MW. Through investigation of the variation of the varied percentage errors, the maximum error attained by ARX is around 12%, whereas the NARX is around 6%.

Jurado et al. [50] have proposed Hammerstein models for micro-gas-turbines to support the dynamic performance of micro-GT in distributed generation. The proposed nonlinear identification has been divided into linear part of the model and nonlinear part of the model. The linear part is a rational transfer function with unknown parameters and the nonlinear functions are polynomials with a known order and unknown parameters to be estimated. The model parameters are identified through comparison with experimental data and simulations of a physical model. Time-based simulations and Bode plots have confirmed the model validity.

Mohammadi et al. [51] have introduced a new method for the gray-box identification of enhanced Wiener models (EWM) for GT. It has been shown that Wiener models embed very low computation burden while preserve high accuracy. This is a very hard duel advantage to be achieved by other models and the depicted results in the paper have clearly shown the superiority of gray-box identification of Wiener models over other identification techniques, such as NARX and the adaptive network-based fuzzy inference system (AFINS). The least squares method (LSM) has been used to optimize the model parameters. The reference frame responses for this comparison hasn't been adopted from the real measurements, instead, it has been extracted from the detailed thermodynamic model. The proposed identified Wiener models have given satisfactory agreement with the smallest percentage errors and tracking of the variation trends of the power generation GT. The nonlinearity has been introduced static element interconnected with linear dynamic systems in order to relate the fuel flow rate to the exhausted temperature and other variables of the system, and the unknown parameters of the whole system have been identified using the black-box technique.

Abdollahi et al. [52] have proposed multi-linear ARX model to compensate the nonlinearity nature of V94.2 gas turbine and the model parameters have been identified using the LSM. The model structure has been eventually presented as 6 rational transfer functions in z-domain that covers 6 operating regions of the GT from 20 MW to 160 MW, where each region is responsible for capturing a 20 MW range of operation. Moreover, the multi-linear model has been compared with another nonlinear simulator for time-based dynamic responses with reasonable agreement that confirms the success of the proposed technique. The adoption of multi-linear models has been additionally justified through Bode plot results

Mohamed et al. [53] have presented linear system identification approaches for constructing GTPGP state-space models. Two methods have been used and compared, which are the numerical subspace state-space system identification (N4SID) method and the prediction error method (PEM). The N4SID is found to be faster in identification procedure, which indicates the suitability for on-line identification of the process. N4SID is mainly based on advanced concepts of linear algebra, mainly the singular value decomposition and oblique projection of system matrices. On the other hand, PEM is an iterative optimization technique that minimizes the error between the measured and simulated responses and produces the solution of identification in at least 20 iterations. This iterative nature of PEM makes not comparatively slower than N4SID. Nevertheless, it has been proved that the PEM-developed model is more accurate through observation of simulations and residual correlation tests of both models. Both models have been validated by comparing them with real GT data record and by residual analysis. The same GT in [53], with a different set of data, has been used by the same primary author and other co-workers to develop another linear identified model using the canonical variate algorithm (CVA) based subspace identification, with more inputs and outputs [2]. Again, the time-based simulation results depicted have indicated the model validity as the load varies from 120 MW to 240 MW. The models in [2] and [53] are combined (deterministic/stochastic) on the generalized form state-space equations. In order to satisfy the various noises in the turbine and its measurement devices, the implication on the stochastic part of modeling gas turbine power plants has been justified [2,53].

Holcomb et al. [54] proposed subspace identification for GTPGP with its associated control system, closed loop identification, using covariance-based subspace identification for the purpose of disturbance rejection control. The data has been gathered from another simulator based on first

principles or physical principles. The model has been validated over a specified operating range using step responses, which are the shaft speed, the turbine inlet temperature and the compressor outlet temperature. The measurement noises have been incorporated as Gaussian noises with zero-mean.

More recently, Pandey et al. [55] has extended the work in [54] to perform multi-stage cascaded subspace identification, in which the output of the first stage has been used as input for the second stage. The model has been validated over wide operation range using residual analysis, Bode plots, and time simulations with accuracy of 86.34% for the temperature signal.

Xu et al. [56] have introduced three-stage identification procedure to capture the behavior of a micro-GT with saturation effects. The focus of this study elaborates into the effect of micro-turbine on the distribution network. The three stages involve: (1) preprocessing of data and estimating the state-space model order; (2) model identification via N4SID technique; and (3) incorporation of saturation effect, if exists, and add it as upper bound incorporation to the sequence of states. Simulations have indicated promising performance of this method as it is mixed between linear state-space models in addition to the nonlinearity effect of the saturation. The saturation has been included as a nonlinear expansion of the piece-wise linear models of the micro-turbine.

Kulikov et al. [57] have introduced a Markov stochastic model for a gas turbine power plant for the purpose of energy efficient control. The data set has been extracted from a gas turbine test rig. The concept of final phase trajectory of Markov Chain has been used to construct the model. The fuel flow is regarded as an input and the shaft speed or frequency is regarded to be the system state. Other external influences are regarded to be a random disturbance.

The main aspects of each identification and model structure are fairly justified for each group of models, both linear and nonlinear. While more accuracy can be obtained from nonlinear identified models, the linear identified models have broader control system applications [58]. Simplicity of linear SI has paved the way to more practical achievements in control industry. The adopted reported models have been widely considered and accepted to be compliment to each other. Table 2 summarizes the identified models of gas turbine generation systems. In the next section, the artificial neural networks (ANN) models are investigated.

Table 2. Summary of GT SI models.

Category	Model structure	Identification Algorithm	References
Nonlinear	Wiener and Enhanced Wiener Models	Least Square Method (LSM)	[51]
	NARX model	(LSM)	[49,51]
	State space model incorporated with saturation effect	Subspace Identification (N4SID)	[56]
	Hammerstein Models	Not mentioned: It was reported that the parameters found by comparison with physical simulator	[50]
Linear	Linear Discrete-time state space models	Subspace Identification Algorithm (mainly N4SID)	[2,53–55]
		Prediction Error Method (PEM)	[53]
	ARX and z-domain transfer functions	Least Square Method (LSM)	[52]
	Markov Modeling	Moore-Penrose Pseudo-Inverse in least square sense	[57]

3.2.2. Artificial Intelligence (AI) and Machine Learning Modeling

Artificial intelligence applications have proposed many solutions for gas power plants' problems concerning monitoring, predictions, fault diagnosis, and control [59–65]. The most popular approach of AI in this field of study has been the ANN. There is a variety of methods within ANN

classification and they have been applied to GTPGP with emphasis on different practical problems and turbine characteristics.

Asgari et al. [59,60] have constructed another different NARX–ANN based model for capturing the startup process for a General Electric PG 9351FA GT. Neural Networks Toolbox has been utilized to build-up the NARX model. The time-series data has been divided into six subsets, in which three of them have been used for training and the other three sets have been employed for validation. The capability of ANN has been proved to capture the whole process of startup of the practical GT. The model has been tested to capture four important outputs, which are the rotational speed, the compressor pressure ratio, the compressor outlet temperature, and the turbine exhausted temperature. The maximum percentage root mean squared error (RMSE) is around 7.4% for the compressor pressure ratio [59]. The results in [60] have proved better of NARX–ANN model than physics-based model for simulated outputs.

Elashmawi et al. [61] have presented multi-layer feed-forward ANN to capture the process of GT for detecting the degradation in the efficiencies in the major components of the power plant. The ANN has been implemented as a graphical user interface (GUI). The performance of ANN for tracking turbine deteriorations has been proved with around 99% accuracy.

Mohamed et al. [22] have shown the capability of back-propagation (PB) feed-forward ANN to predict three significant variables in the GT, which are the exhausted temperature, the output power, and the power system frequency. The hyper-parameters of the ANN have been manipulated to ensure the best performance. It has been proved that the ANN is generally more accurate than other approaches, which are the physical model and subspace-based SI model, because it has the ability to depict the nonlinear nature of the turbine. The maximum NRMSE has been noticed to be 3.9% for the power response. Despite the ANN superiority of accuracy in power signal, it hasn't been efficiently capable to depict the small excursions of the output frequency with the same accuracy of other modeling approaches because the ANN have naturally rounded up and down these small variations and rapidly stagnated for the frequency excursion responses.

Rashid et al. [62] have proposed a novel technique for training the feed-forward ANN by particle swarm optimization (PSO). The purpose of that study has been to predict the energy production from a CCGT. Enormous sets of data have been used, in which 70% of them for training and 30% of them for validation purposes. Promising results have been attained for the power response, which has been the only output in that research, with a mean squared error (MSE) of 0.005. However, some meteorological variables have been considered as inputs instead of some significant control inputs the CCGT such as the control valve position or the fuel flow. This confines the model application into long-term prediction and reduces its suitability for control applications.

Talaat et al. [63] have published feed-forward ANN for prediction of a 125 MW GT power plant performance deterioration. For unrelated reasons, the deterioration in efficiency may happen in the main components of the gas generation plant, such as the compressor, the combustion, the turbine, and the air capacity efficiencies. That paper offers the two successful structures of ANN, with single and multi-layered ANNs. The degradation data sets for the training the ANN has been generated by thermodynamic model. In the validation phase, the maximum error noticed has been for emulation of the axial compressor efficiency deterioration, which was just 5.02×10^{-4}. However, the model is suitable for dynamical performance evaluation rather than control system design.

Boccaletti et al. [64] have proved the suitability of BP feed-forward ANN for on-line control of gas turbines through their fast computational nature and proper selection of the output variables. That research has been carried out on a practical co-generation plant, but the training data sets were collected from detailed physical simulator. Wide range simulations confirmed the capability of the structured ANN to compute the outputs in with high accuracy and very short time.

It can be deduced that the tendency of researchers and experts in the field is towards the feed-forward ANNs due to their simplicity. Different architectures of ANN, such as radial basis networks (RBN) has been proposed for GTPGP diagnostics and fault identification and compared with feed-forward BP ANN [65,66]. However, it has been concluded that it is not quite necessary to

change from feed-forward BP ANN to RBN [66]. The adoption feed-forward BP ANN for modeling GTs has been then justified by tracking their performance over the selected articles as some of them were published recently and others published several years ago.

Further investigations of the literature have brought another machine learning approach, which is found to be very useful for condition monitoring of GTs. In this context, other representative method is discussed. Enríquez-Zárate et al. [67] have presented modern and contemporary genetic programming (GP) methods for automatic modeling of Mitsubishi single shaft Turbo-Generator. GP is presented in such a way to automatically derive the GT model structure. Local search mechanism has been integrated with genetic programming that lead symbolic models, which evolve in the search process, for fuel flow and exhausted temperature, with 33 identified parameters for the fuel flow model and 38 indentified parameters for the exhausted temperature model. The proposed approach has been compared with other machine learning methods in order to show its superiority. However, the generated power simulations are not provided in that paper.

In the next sub-section, the classical simplified mathematical models that were developed many years ago are discussed.

3.3. Simplified Mathematical Models

The most popular heavy-duty GT model is the well-known Rowen's model presented in 1983 [68]. The model represents the General Electric (GE) GT for the purpose of power system stability studies. Simple representation of the model in blocks' diagram, with its associated controllers, and the availability of all its parameters have given the simplicity feature that further stimulates the GTPGP to be an active research area for GT control system development and power system dynamic performance studies. The fuel preparation system has been considered as two cascaded first-order transfer functions with internal loop gain and its output is linked to classical complex exponential function in s-domain to emulate the combustor time delay. The model consists of constant gains, limiters, integrators, summing nodes, and transfer functions. The model coefficients are found through comparison with steady state practical operation and have been given as English and metric units. However, the model is modifiable and the parameters can be normalized for pu system representation with other off-line tests to find the governor droop [69]. Other versions of simplified representations can be found in [13,70], which implicate some thermodynamic equations and different controls to formulate a hybrid version known as the IEEE model. These simplified models are very suitable for dynamic performance studies and control development and the other candidates of models in Sections 3.2 and 3.3 are developed with emphasis on improvement of GT by other influencers/inputs that may not exist in these simplified versions. For example, the pilot-valve can be included as an additional input that can be manipulated with the natural gas (NG) valve to stabilize the combustion in the premix and ensure. Moreover, the assumption of fixed compressor pressure ratio in the simplified versions of IEEE models [7,70] cannot be feasible when the control system objectives are elaborated to include optimum energy efficiency objective. One of the best ways to attain higher GT efficiency is through achieving higher compression ratios, and consequently it cannot be regarded as constant for modeling-based efficiency improvements. The diversity of modeling gas turbine power plants can be appreciated through investigation of the research objective and the latest operational requirements for achieving higher GT efficiencies and optimal dynamic behavior. In summary, a critical review for modeling has been briefly given and the next two sections discuss the review of control strategies of GTPGP and the proposed new trends, respectively. The most cited model among all other models is Rowan's model, which contains some processes graphically represented as blocks' diagram in Reference [68].

The author's research article [22] summarizes a preference comparison that has resulted from research simulation results, which result in an independent qualitative comparison between the three approaches. The simulation results have been reported as an independent study between the main modeling approaches for different significant variables of the various power plants in descending order. As stated earlier, the comparison between models in the published papers will not be reasonable

enough due to the difference in the operating data that heavily influence the accuracy of the models. Because the data in [22] is for a specific GT, the comparison in this way becomes rational.

The model outputs will be individually discussed. It is important to mention that, the generated power simulation is best depicted by the feed-forward ANN and other machine learning techniques in general, as they are more capable of handling the large variations of the plant operation, in which the system is likely to be operated. On the other hand, frequency variations have shown superiority of the physical models due to their physical insight and SI techniques due to their appropriate mathematical structure for simulating frequency excursions over the feed-forward ANN that stagnated around the nominal frequency. The deeper reason behind this is revealed, it is well-known that the frequency changes affect the turbine more than the generator dynamics because of the turbine mechanical resonant tenseness that may happen as a result of deviations from synchronous speed, especially during underfrequency situation, such physical interactions are better to be represented by physical models and SI techniques. In the validation phase of frequency simulations, physical models usually outperform the other two approaches as it preserves its thermodynamic and mechanical nature for effective emulation of the frequency changes. The exhaust temperature is better represented by physical model tuned by optimization algorithm because the variations in temperature around the set point are small, these variations have been automatically rounded up or down by the feed-forward ANN as the case of frequency small variations.

However, this comparison in has been for the feed-forward ANN. It is important to mention that, the performance of the recurrent NARX ANN models have shown better performance than physics-based models for simulations of the rotational speed of the turbine (i.e., the frequency) and also the exhaust temperature of industrial power gas turbine [60]. The last category of simplified mathematical models is not intended for this comparison because there is no yet reported research article has brought them in the same time window with other techniques for the selected variables in the same system.

In summary, a critical review for modeling has been briefly given and the next two sections discuss the review of control strategies of GTPGP and the proposed new trends, respectively.

4. Control Strategies for Gas Turbines Power Generation

The design of control strategies for GT power generation systems has many objectives that cover control theory requirements and other industrial requirements. This paper offers a survey for some significant achievements in the field with considerations of the control hierarchical structure and the resultant operational improvements. Digital control systems have grown rapidly in recent decades, which are generally based on closed loop modeling and identification and subsequent two main levels of control: supervisory and regulatory levels. The most popular technology found in the literature that provided feasible results are the model predictive control strategies [71,72]. Model predictive control (MPC) has become a dominant approach for modern control of power plants because it naturally handles the practical operation restrictions or constrains and apply the mathematical optimization of the future signal to fed it to the plant at the earliest possible time. Thereby, the closed loop system exhibits more kinetic energy to release quicker responses in the outputs. Two common configurations are found in the literature to apply the multivariable modern control on the plant with its existing local controllers, which are the reference correction (RC) and action correction (AC) configurations shown in Figures 6 and 7, respectively. This classification is mandatory in order to have sufficient philosophy to suggest novel trends in the field.
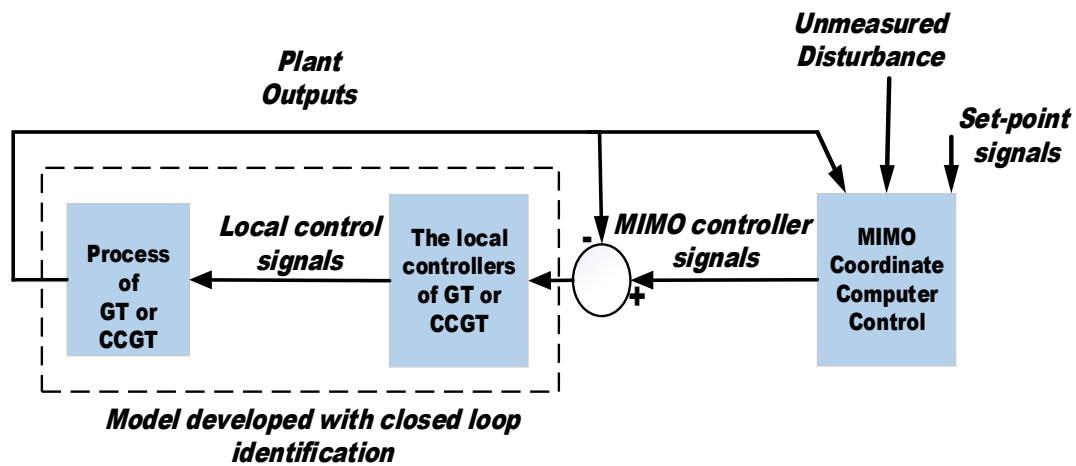
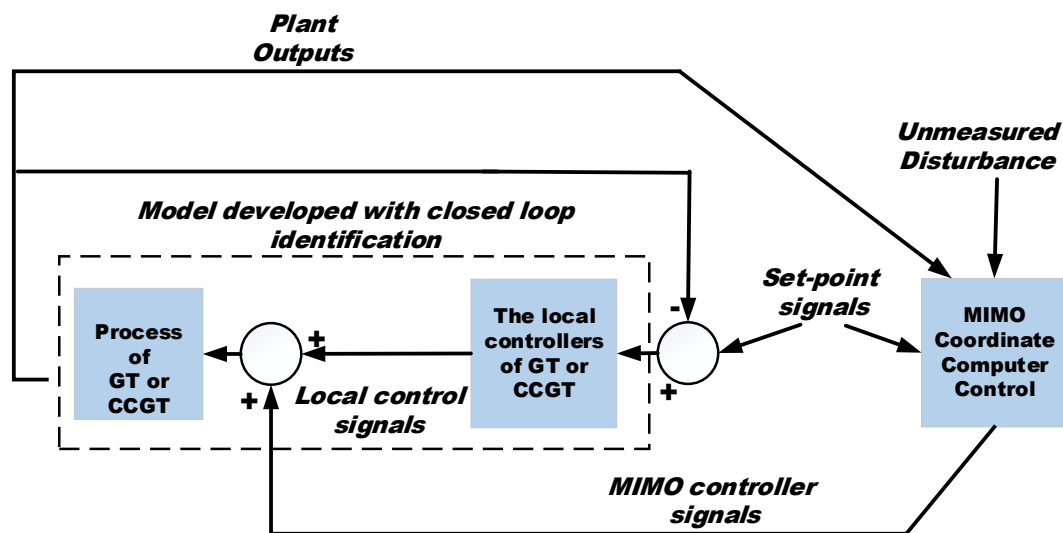**Figure 6.** Supervisory control with *reference* adjustment.

Figure 7. Supervisory control with *action* adjustment.

In discussion of the scientific papers published, many strategies were found to be useful to optimize the behavior of GT or CCGT during startup and load-following operating modes.

Tica et al. [73] have presented hierarchical nonlinear model predictive control (HNMPC) for optimization of the startup process of CCGT. The control strategy configuration contains two layers: optimization problem in the high level that optimally has computed the load profile for the GT and another low optimization level that is concerned with the MPC problem, which is based on receding horizon principles to refine the load profile. The predictive nature of the NMPC for the process variables is a key aspect to speed up the process, because the signals can be sent in advance. The differences between NMPC and HNMPC were noted to be small in the load profiles, but apparent in the computation time that has proved the capability of HNMPC over MPC, with different horizons of control and prediction, for optimizing the startup process time while keeping reasonable computation time on a PC with 2 GHz CPU.

Jurado et al. [74] have designed MPC for enhancing the stability of the power system. The model that has been discussed in 3.1, which is in [50], has been used as a plant to design the MPC with RC configuration. The whole system has been integrated with an IEEE 13 node test electrical network to illustrate the positive effect of MPC on enhancing the system stability. The MPC has gained simplified linearized internal models, whereas the plant is nonlinear. This has led to very small improvements in the responses with and without MPC because the capability of linearized discrete-time MPC is limited

to the linear operating region whether it is linearized by Jacobian matrix or identified from operation data set.

Sáez et al. [75] have proposed a fuzzy predictive control strategy that is based on genetic algorithms to control a GT of a CCGT. In the initial design, the parameters are regarded to be constant, then updated in the second design for each prediction and GA has been used to solve the nonlinear optimization problem. This strategy is to provide the optimal set-point adjustment, so it has been of RC type and has given promising results for regulation performance. Sáez et al. [76] have used both strategies AC and RC with different names, centralized and decentralized, respectively, again for CCGT. The results have been highly satisfactory, which show the physical performance of both strategies. However, from technical view-points, the decentralized, or RC is safer and more flexible for the plant operator where the regulatory level controller are maintained, which are well-known operators, and the AC strategy is more complex as seen from that side.

Poncia et al. [77] have applied the AC configuration using linear model predictive control to CCGT. The linear model is state-space combined (deterministic/stochastic) identified using the subspace identification technique with highly accurate results. No mathematical details have been given about the subspace method, and the MPC has been applied to the model that includes the plant with its built-in classical regulators. Significant improvements have been observed when adding the MPC, and the structure of the controller seems quite flexible. However, the argument of practical flexibility disagrees with has been discussed in [76], which have given advantageous conclusions for the decentralized or RC strategy, instead of the AC strategy. However, the arguments for trade-off between AC and RC strategies for practical issues, especially safety and simplicity to operators, can be confirmed only during practical commissioning tests of the strategy and the off-line simulations are capable only of guessing the control performance to the electric grid obligations.

Hou et al. [78] have presented another novel Fuzzy predictive control strategy applied for a gas turbine in CCGT. The Fuzzy strategy has been based fuzzy selection mechanism and simultaneous heat transfer search (SHTS). The system provides the optimal set-points for the inlet guide vane (IGV) and the optimal fuel flow, which can be considered as RC strategy as in the classification adopted in this survey. Wide range comparative analysis has been provided with other technique in order to justify the usage of SHTS based fuzzy predictive strategy. The model format is discrete time identified state space model.

Mohamed et al. [3] proposed a linear MPC applied on a subspace state space model of GT operation as a part of CCGT. The philosophy of the control system is that if the optimal reference position for the compressor pressure ratio is predicted in advance, the whole system will exhibit higher kinetic energy to release faster responses on the output, which in turn will enhance the energy efficiency of the CCGT. The strategy has three inputs including the reference corrections (i.e., RC strategy) for the compressor pressure ratio, the natural gas (NG) control valve position, and the pilot valve position, whereas the outputs were the exhausted temperature, the frequency, and the power. The system format has been state-space with stochastic part. N4SID has been used with rather complete mathematical details. The target is to regulate the power according to the demand with maintaining high pressure ratio for the compressor. The energy efficiency of the CCGT has been compared with and without MPC and an improvement of 1.1% in the overall plant efficiency has been attained. However, despite the industrial value of the controller, more accurate results could be attained if nonlinear MPC is utilized.

Rosini et al. [79] have applied MPC on a nonlinear heavy-duty GT model and have resolved the issue of nonlinearity by successive linearization. The control actions have been applied directly on the plant as two signals, the air flow and fuel flow. It can be readily ranked with the AC category of control strategies. The trade-off between MPC, PID, and feed-back linearization (FBL) techniques has been investigated by the time-based dynamic simulations with extensive variations of the external set-points. The results have indicated the superiority of MPC over PID and others, with faster responses and therefore higher energy efficiency with larger areas under the power-time curves. Other interesting

contributions for predictive control are applied on a large-scale GT and micro GT [80–82]. Although it is clear that the dominant approach for GT control is MPC, some other algorithms have been proposed.

Bonfiglio et al. [83] have rather used sliding mode control (SMC), in which the signals of the control law are applied directly to the GT system and the results have been obtained from the model of heavy duty Ansaldo Gas Turbine model (AE94.3A4). The control system has shown promising performance for load following from 150 MW to 250 MW as faster response than feedback linearization (FBL) controller and conventional PID controllers. The controller has shown effectiveness also for load reduction from 150 MW to 50 MW.

Smith et al. [84] have introduced adaptive fuzzy control for optimizing the startup process time of CCGT. The objective is to achieve the rated output in the shortest possible time by optimal scheduling of the GT and steam turbine ST in the plant. However, due to the physical restrictions on the variables of the unit, the problem can be mathematically translated to be a constrained optimization problem. Using Fuzzy Logic-based decision-making with adaptive thresholds to ensure optimum startup for the given load-rate alert. This system falls into the RC category of control. 20 startup processes have been simulated, but few simulations have been depicted and very brief mathematical analysis has been presented for description of the model and the control strategy.

Casella et al. [85] have presented different optimization algorithm for the startup process of CCGT. Two dynamic models are implemented and one detailed in the *Modelica* language, and the other simplified in MATLAB/SIMULINK. The former has been used to produce the identification data for the later one. The later simplified model has been used in solving the optimization problem. Again the problem is to satisfy the load profile, or as it has been called in that article, the *GTLoad* signal, which results in the shortest process time, subject to physical operational constraints. The optimization algorithm has given optimal load profile that reaches 90% of the load in only one hour. Moreover, the procedure is applied on both, the detailed and simplified models with promising results for the constrained variables, mainly the pressure and temperature.

Camporeale et al. [86] have demonstrated the performance of the one-step-ahead adaptive (OSAA) control technique for gas turbine power plants. This controller is based on an updated linear model developed each time step t, then the control law has been derived by rearrangement of state variables' equation followed by least squares estimation of the system parameters to obtain the control signal that minimizes the error between set-point and actual signal. The adaptive nature of the linearized model resolves the issue of excess computation demands. Through observing the proposed scheme in that article, it can be clearly seen that this controller is of the RC or reference adjustment type for two main variables, which are the inlet guide vane (IGV) positioner of the compressor and the other is sent to the fuel preparation system, whereas the output variables have been the exhausted temperature and the rotor speed or frequency. Nevertheless, for complete process control, the system should be upgraded with one more significant output, which is the real power output; however, this requires the addition of one more input to make the control system viable.

Oland et al. [87] have used nonlinear backstepping controller for GT control with relatively smaller load variations in load following mode.

In summary, the output faster response is found to be key feature for MPC because of its predictive nature and execution of optimal future signals and time delays associated with the system can be compensated. The applications of MPC are justified due to its promising performance as linear MPC or NMPC. However, trade-off between both of the algorithms depends on two mandatory features, which are: the accuracy and the computation requirements. It is widely recognized that the linear MPC has lower computation demand than NMPC, whereas the NMPC covers wider range of operation. However, with the advent in computing, automation, and machine learning techniques; the issue of the computation burden becomes solvable, and thus advantages of NMPC overcome its drawbacks. The linear MPC is also viable due to its simple structure and lower computation requirements, but methods are needed to compensate the nonlinearity and noises in the plant, these methods include multi-linear local models, linear models embedded with unmeasured disturbances, or using on-line

identification of the process output. It is also important to mention that, the tests that have been made on the various control approaches, in all aforementioned contributions, have been apparently constrained to simulation studies. There is a lack of experimental validations in the literature of the control methods, which can be done either on a laboratory testbed or on a GT used in practice. However, since the applications are made as simulations on validated models of large-scale GT units, the extension to practical applications is limited due to economical constraints. However, a control system feasibility study can be sufficiently confirmed through application in verified models as stated above, which have given promising simulation results. The practical applications in laboratory testbeds seem to be an additional validation procedure for the perfection of control strategies for gas turbines.

5. The Proposed New Trends

Because of the dramatic growth of GTPGP in recent decades there are still many opportunities to carry out research with the aim of improving the performance of GTs. These are some points to be suggested as future work and recommendations for researchers who are working in the area, which are as follows:

1. For instance, for first-principle models, there are many of these models that have distributed parameter models, lumped parameters, or mixed lumped/distributed according to the model reported assumptions, and some of these physical-based models have lumped parameters tuned by multi-objective optimization. Our suggestion is to employ other state-of-the-art optimization techniques that haven't been applied before, such as: ant colony optimization (ACO), artificial bee colony (ABC) optimization, PSO, the gravitational search algorithm (GSA), and so on. These techniques can be used to revisit the model lumped parameters to attain more accurate results. Some of these techniques are defined as follows:

    - **Ant Colony Optimization**: ACO is a population-based meta-heuristic algorithm that was inspired by and stimulated through consideration of ant colonies. It has a world-side promising performance for industrial systems and can be efficiently applied to tune the model parameters and investigate its optimization performance in comparison with GA. A relevant suggested textbook for ACO for preliminary researchers is suggested [88]. Some successful recent industrial applications can be found [89,90]. Henceforth, it is expected that ACO is capable of making significant improvements in GTPGP model parameter identification.
    - **Artificial Bee Colony Optimization**: this is another population-based optimization algorithm, which is based on the intelligent behaviour of honey bees. Both the ACO and ABC algorithms are related to heuristic methods, but they have some differences in velocity of computation and accuracy depending upon the application. This issue can be further investigated by one of them, or both can be used then in refining the simplified GT model parameters.
    - **Particle Swarm Optimization**: although it has been proved that GA is more robust than PSO for identification of coal mill model parameters [91], further investigations are required on GTPGP models because coal mills are slower in dynamics than GTPGP. Because the GTPGP models embed much faster dynamics and time variations than coal mill models, the PSO is expected to outperform GA in case of GTPGP model identification. This major difference in the responses between dynamical systems opens the way for further investigations between GA and PSO to discover which is truly more robust for parameter identification problem of GTPGP models. This highly interdisciplinary research combines between two different experiences in intelligent computing and power generation disciplines and allow extracting some advantages and drawbacks for each method.
    - **Gravitational Search Algorithm**: this method is based on Newton's theory of gravity between masses. It has been recently used for identification of unknown parameters of induction motors and proved to be much better than other evolutionary computation

techniques [92]. It could be an interesting research area for GTPGP model parameter identification. It is still unclear whether the GSA method will outperform other evolutionary techniques for identifying the parameters of thermodynamic systems like GTPGP.

2. For the empirical techniques of modelling, deep neural networks (DNNs) can be a future research area to pursue and overcome some of the limitations in the conventional ANN. DNN has more multiple layers between the input and output layers, which are expected to computationally handle a wider range of data analysis in the training and validation phases.

3. There is a lack of models describing the startup and shutdown processes. The applications of control in load-following mode are far more than startup process. The starting and forced outage shall be optimized with the shortest possible time form safe, economical, and commercial operation. Data-driven models with advanced SI techniques can be very useful in this task as they have natural suitability for control implementation and can be incorporated with uncertainties with ease. The optimization of the startup process can be either linear or nonlinear. At the beginning of the startup process, under assumption that the system is still not driven enough into the nonlinear region of operation, the startup process can be optimized via linear MPC to gain faster computation demand than the NMPC. This is another significant point to be considered as a future research opportunity, and the whole implementation procedure can be easily done by MATLAB. Two startup process sets of data are needed for the same GTPGP to identify and validate the model, and then optimize the process via classical discrete-time MPC to integrate the GT into the grid at the earliest possible time. The HNMPC proposed in [73] is nonlinear, so the alternative suggestion to attain a lower computational burden is either to use classical MPC and linear subspace identification of the internal model or trying other algorithms of MPC, such as explicit MPC.

4. For deep technical analysis of the control system in load-following mode, some algorithms can be suggested. Intelligent nonlinear controls, like ANN, have indicated lower optimization time when they act as NMPC. However, the small variation trends of some variables, such as the grid frequency, cannot be precisely captured by ANN due to rounding-down and -up of these small variations with the corresponding values of the training data during computation of other set of data. However, the state-space based MPC has considerable capability to handle this problem and other modern control techniques are available. In control theory, the linearized states-space model and the robust control theory are used to derive a stabilising controller to handle the nonlinearity and the uncertainty. H2 and H∞ can be applied to derive stability conditions in the form linear matrix inequalities (LMIs). NMPC based on the extended Kalman filter (EKF) has been applied previously in an oil-fired power plant [93]. Moreover, comparative study of SMC and MPC in GT control seems to be a possible forthcoming research proposal.

6. Conclusions

This paper presented a critical review in the form of a comprehensive survey of GTPGP modeling, identification, and control. Great effort has been expended to report the proper classifications of modeling approaches and categorize them within these classifications. The various system identification techniques applied to GTPGP are discussed in detail and the features of each method have been shown. Both linear and nonlinear SI models were found to be promising in capturing the main dynamical variations of the GTPGP. Furthermore, a separate subsection has been devoted to neural network models, as a class of empirical models, due to their computational differences with SI techniques. Simplified mathematical models are also discussed that have been repeatedly used for stability studies. The feasible control strategies have been reviewed and all were found to fall in two classifications that are both promising to the future industry of GTs. Both the theoretical and philosophical contributions have been discussed with regard to many significant objectives. The GTPGP is an important component of the power system, and the essential reasons for their primary position in power generation technologies are the advancements in its modeling and control methodologies,

which in turn lead to higher efficiencies of GT and more flexible operation. Future research directions have been suggested that pave the way for future researchers to continue progress and development in this field. Future trends are divided into points and sub-points and discussed in detail, which suggests the future challenges for research in this field.

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