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HT-TPP: A Hybrid Twin Architecture for Thermal Power Plant Collaborative Condition Monitoring

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Abstract: Thermal power plants, TPP, are one of the main players in the phosphoric acid and fertilizer production value chain. The control of power plant assets involves considerable complexity and is subject to several constraints, affecting the asset's reliability and, most importantly, plant operators' safety. The main focus of this paper is to investigate the potential of an agent-based digital twin architecture for collaborative prognostic of power plants. Based on the ISO 13374:2015 scheme for smart condition monitoring, the proposed architecture consists of a collaborative prognostics system governed by several smart DT agents connected to both physical and virtual environments. In order to apprehend the potential of the developed agent-based architecture, experiments on the architecture are conducted in a real industrial environment. We show throughout the paper that our proposed architecture is robust and reproduces TPP static and dynamic behavior and can contribute to the smart monitoring of the plant in case of critical conditions.

Keywords: digital twin; agent-based engineering; collaborative prognostics

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Citation: Ghita, M.; Siham, B.; Hicham, M.; Amine, M. HT-TPP: A Hybrid Twin Architecture for Thermal Power Plant Collaborative Condition Monitoring. *Energies* **2022**, *15*, 5383. https://doi.org/10.3390/en15155383

Academic Editor: Tim Walmsley

Received: 16 May 2022
Accepted: 16 July 2022
Published: 25 July 2022

1. Introduction

To fulfill sustainability goals for thermal power plants (TPP) several industrial companies within the energy sector are currently trying to settle new closed production loops, which considers value creation from the intersection of multiple streams involving new value chain and different energy networks of producers, consumers and prosumers [1]. This transition results in the need for the development of flexible and generic approaches for TPP modeling, simulation, and monitoring covering new requirements mainly interoperability, intelligence, and autonomy [2]. Recently, digital twins (DT) have stood out at the core of 4.0 technologies with the potential to capture the power plants' environment complex structures. DT, thanks to the use of different industry 4.0 technologies, its various features, and its generic structure, DT allows the establishment of dynamic communication bridges between real systems and their virtual aggregates [3]. Digital twin refers to a digital replica of potential and actual physical assets, processes, people, systems, and devices that can be used for various purposes [4]. Digital twins integrate artificial intelligence, machine learning, and software analytics with spatial network graphs to create living digital simulation models that update and change as their physical counterparts change [5]. Different architectures and models have been proposed to build TPP digital twins based on white, black, and hybrid models [6]. The white box approach consists of exploiting physical rules and knowledge in order to mirror plant systems' static and dynamic behavior and to represent their complex structure that depends on the interactions of several domains including electrical, mechanical, and thermodynamic principles. The black box approach consists of collecting data and information related to the physical twin within its environment using different sensing technologies, data analysis, and machine learning methods, and deriving based on its various results that can accurately and promptly represent the states of physical systems at present and in the future. Through neural network models, new correlations can be detected and represented between systems variables in order to model assets' deterioration modes and evolution, thus reducing the complexity resulting from the integration of various physics-based models. Hybrid grey box models combine the two approaches [7]. The main purpose of this consolidation is to leverage black box models for their enhanced real-time computing performances and to merge them with White-Box models that provide a degree of interpretability needed for business decision-making and communication of recommendations to the users of the systems [8].

Interoperability can be defined in the context of DT by the ability to communicate and interact with several physical and virtual entities according to a semantically coordinated information and modeling structure of both virtual and real environments [9]. Interoperability requirements include data management and information modeling aspects as well as technical communication constraints. The second category of concerns is summarized by the autonomy that relates to the DT meta-model and main building components and resources, it includes citing a few maintainability and sustainability, security, and operational safety concerns [10]. The last identified category is intelligence as an imminent deduced part of autonomy it deals with DT's abilities to monitor its environments and its physical twin needs and constraints proactively. Intelligence is acquired by learning from and through the environments in order to develop self-awareness as well as predictive behaviors [11]. Two aspects of intelligence are depicted in this context, individual and collaborative intelligence. These three aspects according to these configurations can be captured by the introduction of Multi-Agent Systems (MAS) which offers a flexible, distributed, and smart platform for complex network management and modeling [12]. Agent-based modeling enables to covers both DT internal structure by focusing on agents' roles, goals, and behaviors and networks organization through the establishment of agents' DT societies concept and the development of a collaborative learning environment for closed production loops of TPP [13]. In this paper, we will investigate OMASE-DT in the context of the Moroccan phosphoric acid and fertilizer production chain, and specifically, our case study will cover TPPs that supply electrical energy and medium pressure (MP) and low pressure (LP) steam to production processes.

Each TPP within the industrial complex constitutes an independent island of electrical power generation. The installed TPP capacity is designed to achieve value chain energetic self- sufficiency and to reduce company carbon footprint. Two operating modes are defined for the different TPP of the complex, synchronized and islanding modes. Synchronized operating mode guarantees synchronization to the national grid, whereas islanding mode permits the operation of TPP independently of national grid conditions through the establishment of a virtual incipient link with the plant's internal grid. The transition between these two modes depends on various constraints and drives the operating logic of the producers/consumers network of which TPP is an integral part. Among these constraints are network agents' health state, demand side requirements fluctuations, and finally mode transition detection according to the conditions of the connection with the national grid. Our introduction to the fundamentals behind the concept of OMASE-based DT and the analysis of its different modeling approaches for TPP condition monitoring in the context of this paper led us to the first perspective on their potential contribution to the resolution of its problematics. We formulate these research contributions (RC) according to two axes.

RC1: *Development of a digital twin able to mimic the structure of TPP systems and to simulate their interactions and dynamics through time and space.*

RC2: *Integration of a collaborative prognostic layer with interrogation, prediction, and learning functionalities as described by the combination of digital twins and distributed intelligence at the decision-making system scale.*

The paper is structured as follows: the Section 2 describes business concerns, and DT architecture requirements and introduces the adopted research methodology for DT architecture modeling. The Section 3 describes architecture conceptual design. The Section 4 deals with the presentation of a first prototype of the solution through a specific case study and the Section 5 compares our proposed solution to existing digital twins' architectures for TPP condition monitoring and prognostics. The Section 6 resumes contributions and limitations of the proposed solution and opens up on further research axis.

2. Design Methodology and Approach

2.1. Power Plant Specifications and DT Development Business Concerns

Electricity production at the power plant is initiated by High Pressure (HP) steam flow originating from sulphuric acid production process recovery boilers. Thermal power plant TPP production monitoring is driven by energy and medium pressure steam self-consumption of fertilizers and phosphoric acid production units and the share of energy exchanged with the national grid and the in-house utility network. Exhaust steam is collected in the condenser and sent by recovery pumps to a water treatment system for recon version into water, thus completing the power plant's thermodynamic cycle. Condition monitoring process of TPP is governed by a set of business concerns (BC) that decision-makers have to manage in order to ensure its safe and efficient operation.

The first issue concerns the exploration of TPP status, which depends on the analysis of its agent's status, mainly in this case steam turbine, gearbox, generator, and condensation system, but also of its material and energy flows governing inherent interactions between its elements and the different adapted operation modes. Since this analysis is complicated and requires the acquisition of several parameters during normal and critical conditions, it raises a series of concerns.

BC1: *How can we proactively capture in a robust and real-time manner the complex structure of the elements composing the thermal power plant, their causality, and interconnections through space and time without disrupting their normal operation within the physical environment?*

The second aspect concerns the establishment of a constant link with the network of consumers and producers fed and supplied by the plant. The identification of consumers' demands is intended to guarantee plant efficiency and to assess self-consumption of the local network, and more specifically to manage off-sizing conditions and to shorten control system response time to the foreseeable and unforeseeable changes the of load [14]. Establishing this communication bridge through a physical pathway remains complex and is limited by functional and non-functional requirements and depends on the established industrial and supervisory control infrastructure.

BC2: *How can we establish a constant link with consumers' network agents and thus proactively predict load fluctuations imposed on TPP, and its contribution to industrial complex self-consumption potential.*

The third point, as mentioned, concerns the interactions of TPP with the national grid and the different anomalies that could affect this connection and consequently result in switching the plant to islanding mode [15]. Disturbances on the national grid entail hazards for the personnel and the installation, and it is essential to detect their appearance quickly, to be able to island, to bring the island back to a balanced situation in case of deficit via load shedding, and then to reconnect once they have disappeared. The different steps of this process are currently assigned to the control system and supervised by the operators and maintainers in the field and are experiencing a number of difficulties, resulting in infrequent but critical tripping of the turbine due to overspeed or generator load rejections.

BC3: *How can we support operators in their decision-making process, from the identification of symptoms, the detection of anomaly patterns from condition indicators, through prognosis to the final step of validation and implementation of corrective actions and preventive barriers?*

The last point relates to the development of technological solutions that can be integrated into the existing control and command architecture. Concerns are mainly focused on cyber security and ergonomic challenges. The system's ergonomics directly impact its integration within the industrial site and its adaptability with the current control system, serving as a decision support tool for the site's engineers and as a medium to assist control room staff. To guarantee that the new solution is efficient, a variety of operational, maintenance, and process data must be communicated. This communication is constrained to several networking security requirements.

BC3: *How can we establish an ergonomically secure connection with the different data sources of TPP complex systems and create a new smart and proactive performance communication interface for the various collaborators of the industrial site?*

2.2. An Agent Based Modeling Framework for Digital Twins

The Organization Multi-Agent System Engineering (O-MASE) method, an extension of the MASE method, is part of the OPEN Process Framework integrated approaches for the definition of custom agent-oriented systems development processes [16]. OMASE is one of the MAS development methods that focuses on the integration of the implementation aspect in its proposal of the different views of MAS [17]. OMASE is based on the assumption that a MAS can be represented by a social organization where each agent plays a role according to its capabilities and its internal development model and with the objective of achieving the goals defined by the system requirement structure and the basic foundations of the domain represented within the domain model [18]. The method is articulated around three main phases for MAS development which are requirements definition, analysis, and design, it offers a complete software engineering framework for a MAS that can extend to all lifecycle phases of a MAS [19]. The main concepts that constitute the approach static and dynamic diagrams are organization, role, capability, goal, agent, plan, protocol, and policy models. O-MASE offers through its models a complete framework for the development of MAS views; thus, in this context digital twin architecture building blocks [20]. Through MAS architecture, interrogation, prognostication, and learning aspects can be integrated directly into the definition of different DT Agents. Table 1 represents DT mapping through OMASE views across the literature.

Table 1. DT-OMASE proposed views mapping to OMASE models.

			Augmented OMASE Models		Conducted Work		
DT-OMASE Views	**Concerns**	**Stakeholder**	**Dynamic Diagram**	**Static Diagram**	**Views**	**DT**	**DT-OMASE**
Business View	Integration Context Awareness	Business Team Network	Goal Model for Dynamic Systems GMoDS	Domain model Scenario Descriptor	Environment View	[21–25]	[26,27]
Usage View	Integration Context Awareness	Design and Development Network	State Chart Diagram Unified Modeling Language (UML)	Service model Requirements Document Use Cases Diagram for Agents	Agent Services View	[28–32]	[33–37]
Functional View	Semantic and Syntactic Interoperability Sustainability	Design and Development Network Office Floor Shop Floor Networks	Plan Model	Activity Model	Workflow View	[38–40]	[41–44]
System View	Integration	DT Architects DT Owner DT Technology Provider	NA	Architecture Diagram Role Description Agent Class Model	Architecture View	[45–48]	[49–53]

Table 1. *Cont.*

			Augmented OMASE Models		Conducted Work		
DT-OMASE Views	**Concerns**	**Stakeholder**	**Dynamic Diagram**	**Static Diagram**	**Views**	**DT**	**DT-OMASE**
Networking View	Communication Security Technical Interoperability Maintainability	DT Architects DT Owner DT Technology Provider	Protocol model	Protocol Descriptor Agent Class Model Role Descriptor Organization Model	Agent Society View	[4,54–56]	[57–59]
Information View	Semantic and Syntatic interoperability Traceability	DT Architects DT Owner Digital User	Plan model Action model	Agent Descriptor Capability Diagram	Knowledge View	[60–64]	[51,65]

3. HT Architecture Conceptual Design

Three main phases are considered for Organization Multi-Agent System Engineering Digital Twin (OMASE-DT) architecture development. These main phases are basically inspired from Multi-Agent System Engineering (MASE) approach [16]. Each defined phase is apprehended by a set of diagrams and models that helps to define the basic elements for DT views definition and refinement. The first phase consists of requirements engineering and business concerns definition by project stakeholders. It is developed based on the structuring of business goals and systems purposes according to users' needs definition. It is refined by the introduction of dependencies and views that links different goals through time and space. During this phase, the goal model of dynamic systems (GMoDS) diagram is defined for the architecture. The second phase exploits result from the previous phase in order to define firstly the main roles that are needed in order to achieve the goals of the architecture, and secondly the needed organization and environment features from a macroscopic view. Three main diagrams are constructed during this phase, role, organization and domain models organization model structures the interactions between the architecture and external agents and identify the main communication protocols that helps to establish these interactions. Role model defines behavioral patterns of the organization. The last phase is design phase. It defines low level structure of the architecture and frames detailed specification of its agents and their roles. The main diagrams of this phase are agent class model, capability model, plan model for implementation, and protocol model for the definition of internal interactions between agents. The policy model contains specific rules and constraints that governs agent individual and collective behavior. Figure 1 summarizes this step and gives an overview of the diagrams that are exploited in the three phases defined.

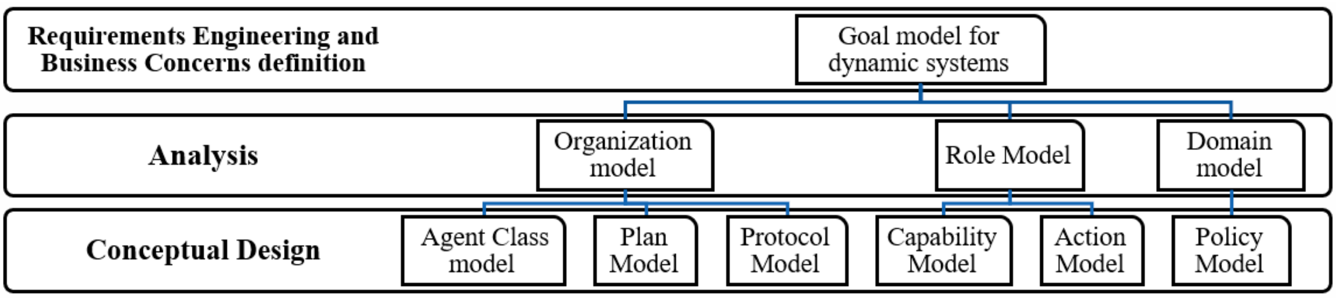


Figure 1. Architecture design approach according to O-MASE.

3.1. Hybrid Twin Architecture Requirements Engineering

Table 2 describes the different requirements formulated based on the identified concerns and interviews with field collaborators and engineers. The two types of requirements (RQ) are defined as operational and functional. The OMASE main models were developed based on these requirements

Table 2. Business concerns for HT-OMASE development.

BC	Derived Requirements	Type	Stakeholders
BC 1	RQ 1.1 Shall simulate the three operating modes of TPP	Operational	Engineering Team
	RQ 1.2 Shall simulate a frequency disturbance from the national grid (above or below 50Hz)	Operational	Maintenance Engineer
	RQ 1. 3 Shall simulate alternator active and reactive powers	Operational	Electrical Maintenance Engineer
	RQ 1. 4 Shall simulate TPP with both design and dynamic data (ideal and real state of the components)	Operational	Maintenance and process engineers
	RQ 1.5 Shall help to reproduce turbine, generator and condenser malfunctioning and failure	Operational	Maintenance engineer
BC 2	RQ 2.1 Shall give predictions about medium steam consumption	Operational	Process engineers and control room collaborators
	RQ 2.2 Shall give predictions about plants units energy consumption and TTP Key Performance Indicator (KPI)	Operational	Top management
BC 3	RQ 3.1 Shall give predictions of turbine and generator health and reliability performances	Operational	Process engineers and control room collaborators
	RQ 3.2 Shall detect root causes of malfunctions in the steam turbine	Operational	Maintenance engineer and control room collaborators
	RQ 3.3 Shall enable testing and validation of new control strategies and maintenance corrective actions	Operational	Engineering team
BC 4	RQ 4.1 Shall integrate the group's current supervision interfaces	Functional	Control room collaborators
	RQ 4.2 Shall be validated by end users and control room operators before use	Functional	Engineering team
	RQ 4.3 Shall respect security and safety standards	Functional	System architects and top management
	RQ 4.4 Shall integrate interfaces to communicate securely with plants PLC, archiving systems and others TPP plants within the industrial complex	Functional	System architects
	RQ 4.5 Shall integrate secure remote access	Operational	Engineering team

Goal Model of Dynamic Systems: O-MASE approach is characterized by a particular focus on requirements tailoring for enhanced analysis of stakeholders' concerns defined earlier as a major component for the development of the architecture. The first two models that we worked on are the first goal model and the goal model for dynamic systems which is a refinement of the first proposed model for goals. The goal model is based on the exploration of the different objectives targeted by the HT-OMASE hybrid twin system. It is formulated through a central goal deployed throughout two subgoals. The first subgoal of overall asset networks (AN) condition evaluation consists of the identification, definition, and evaluation of the main AN health condition indicator with regards to defined targets by AN owners and stakeholders, this subgoal triggers the first level field interrogation process that will be detailed further. The second subgoal consists of the development of an online learning scheme for cooperation and integration of heterogeneous information from AN. Learning of agent is reinforced by the third subgoal of federated learning that is completed offline according to a type instance exchange of acquired experience process. The last subgoal is intended to inform and report the results concluded from all this conducted smart analysis acquired data and deduced knowledge by intelligent agent organization. Figure 2 presents HT-OMASE GMoDS that constitute HT-OMASE business view.

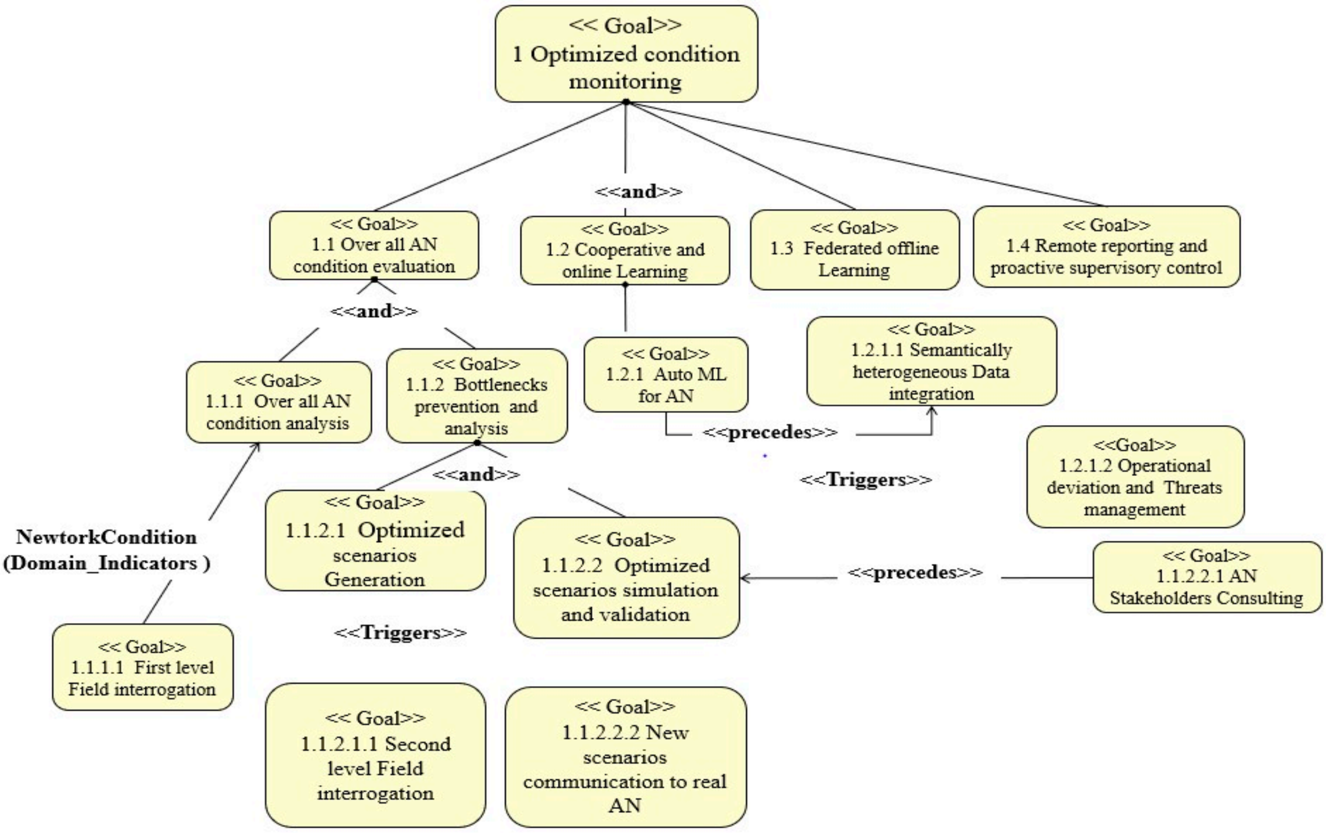


Figure 2. HT-OMASE business view—goal model of dynamic systems GMoDS.

3.2. Hybrid Twin Architecture—Analysis

3.2.1. Organization Model

This phase consists of the development of domain, goal–role–capability, and organization models. The proposed organization model includes the different stakeholders defined as a result of our analysis of the field. External protocol refers to communication links between system organization and its stakeholders' categories in contrast to the internal protocol that links agents' societies external protocol is focused on external links with the environment and its actors which as identified by context influences plays a crucial role for the definition of the internal social platform of a MAS and for DT societies in particular. The model is augmented with a two-fold policy component, behavioral policies that define agent organization policies that include security policies and agent roles allocation policies for goals define basics policies for agent operation throughout the system lifecycle both folds are subject to updates and modification with respect to system evolution and systems metrics requirements changes. Organization behavioral policies are founded on the basis of environment value judgment systems and constraints on agents' plans and capabilities. Agent role allocation policies for goals are inspired by real environment organization of entities, objects, and foundations that are modeled and represented by a domain model that is constructed through domain ontologies. Figure 3 introduces the DT-OMASE organization model.

3.2.2. Goal–Role–Capability Model

In order to achieve defined goals for the architecture DT agents are assigned a set of roles that depends each on several capabilities distributed among actors of the architecture. The collaborative aspects of the organization are achieved by the distribution of responsibilities for goal achievement. For instance, the first subgoal that is first level field interrogation relies on three roles, behavioral mapping, environment observation extraction and condition indicators selection and evaluation. First level field interrogation starts with real environment observations extraction that consists of acquiring observations from the field about the real twin through communication protocols with field interpreters as instance measurement systems. This step is followed by relevant condition indicators extraction and evaluation that require features selection and feature extraction capabilities. Computed condition indicators are communicated to the last phase in the process, which consists of asset behavior mapping. The behavioral mapping role requires two capabilities health index estimation model and classification algorithms. The estimation of assets health index helps to categorize health status of the real twin and initiate if detected to anomalies classification and detailed identification through implemented classification algorithm capability. Figure 4 represents HT-OMASE information view that is represented by goal–role–capability model.

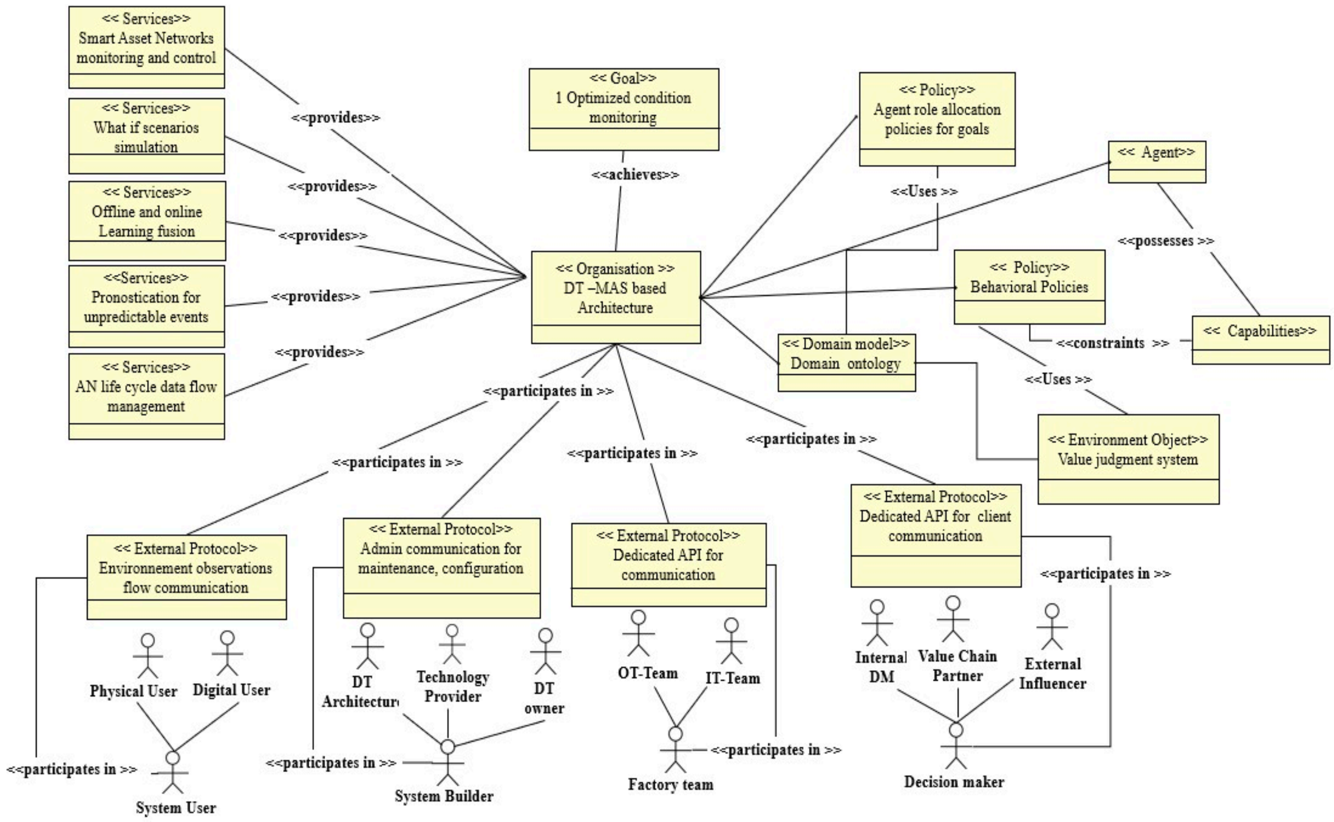


Figure 3. HT-OMASE networking view for the use case—organization model.

3.2.3. Domain Model

As highlighted throughout this paper context establishment for DT business objectives and value tailoring is a major step for DT architectures conception. This particular aspect is apprehended through our paper by the domain model, which is based on our exploration of various domain ontologies related to industry 4.0 and proposed metamodel for Asset Administration Shell as well as standards for definition of systems boundaries for reliability development of complex systems. Our definition of steam turbine boundaries is based on the model proposed by ISO 14224:2016 [66] and OREDA:2005 [67]. These standards, as well as ISO 18434:2008 [68], ISO 20816:2016 [69], ISO 17359:2011 [70], and interviews with plant process and reliability engineers were used for cognitive map definition and impacts of interactions definition. The proposed domain model for the use case aims to enhance DT awareness about its environments by creating a standard representation of basic real system concept and systems of systems. Figure 5 represents the domain model. The health index through the map is estimated based on dynamic and static parameters. The dynamic parameters are represented by health modifiers (thermography, lubrication, vibration, cooling, pipes condition, leakage), reliability modifiers (% downtime; average reliability; overhaul rate; active_repair_time) and load modifiers (load_factors). The static parameters are aging rate (initial_health_index; useful_life), useful life (manufacturer_life; load_factors; location_factors), environment factors (environment_tempearture; distance to coast; exposure_rate; exposition rate). Different levels of influence are defined negatively very strong influence (NVS), negatively strong influence (NS), negatively strong to medium influence (NSM), negatively medium influence NM, negatively medium to low influence (NML), negatively very low influence (NVL), negatively low influence (NL), zero influence, positively very strong influence (PSV), positively strong influence (PS), positively strong to medium influence (PSM), positively medium influence (PM), positively medium to low influence (PML), positively low influence (PL), positively very low influence (PVL). The selection of influence level is defined by interviews with plant engineers and the establishment of different cognitive maps towards a common social cognitive map.

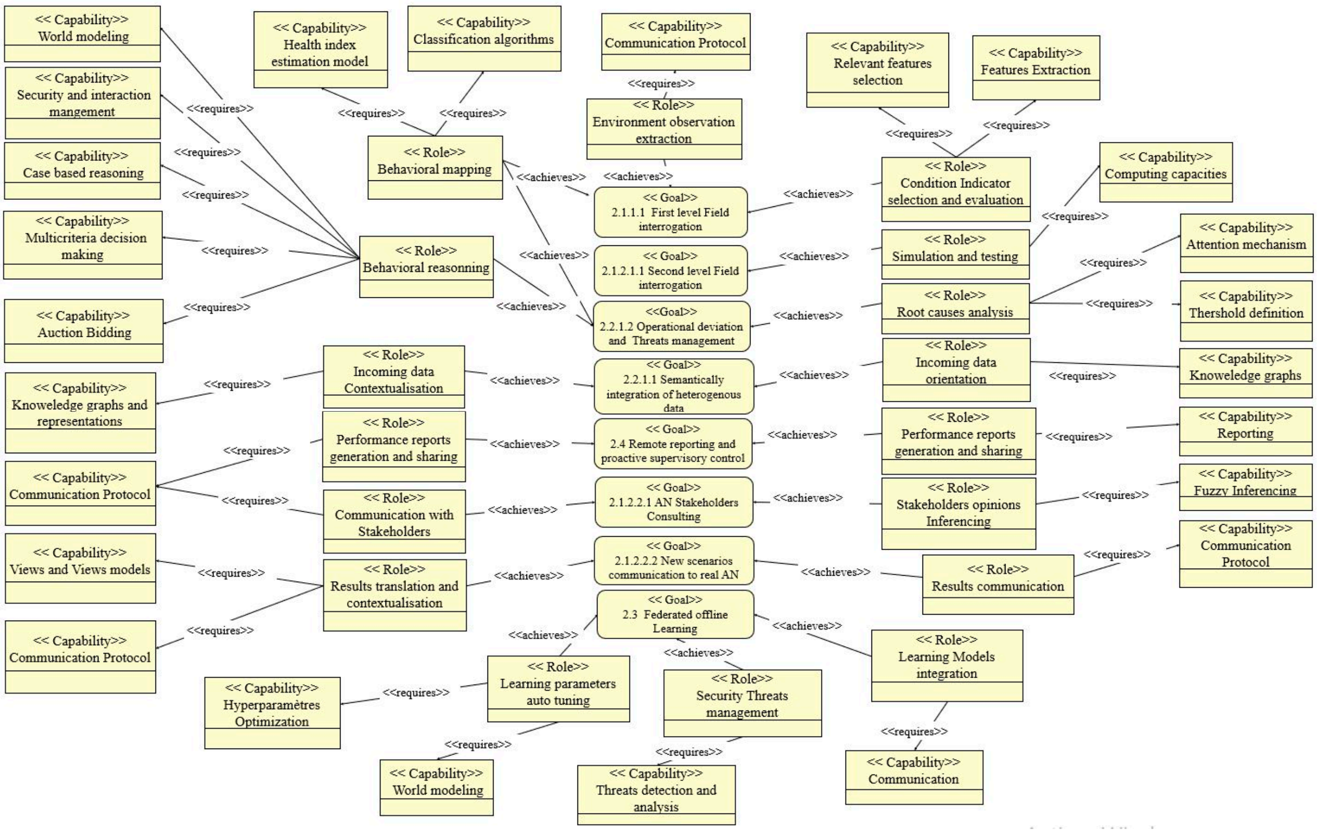
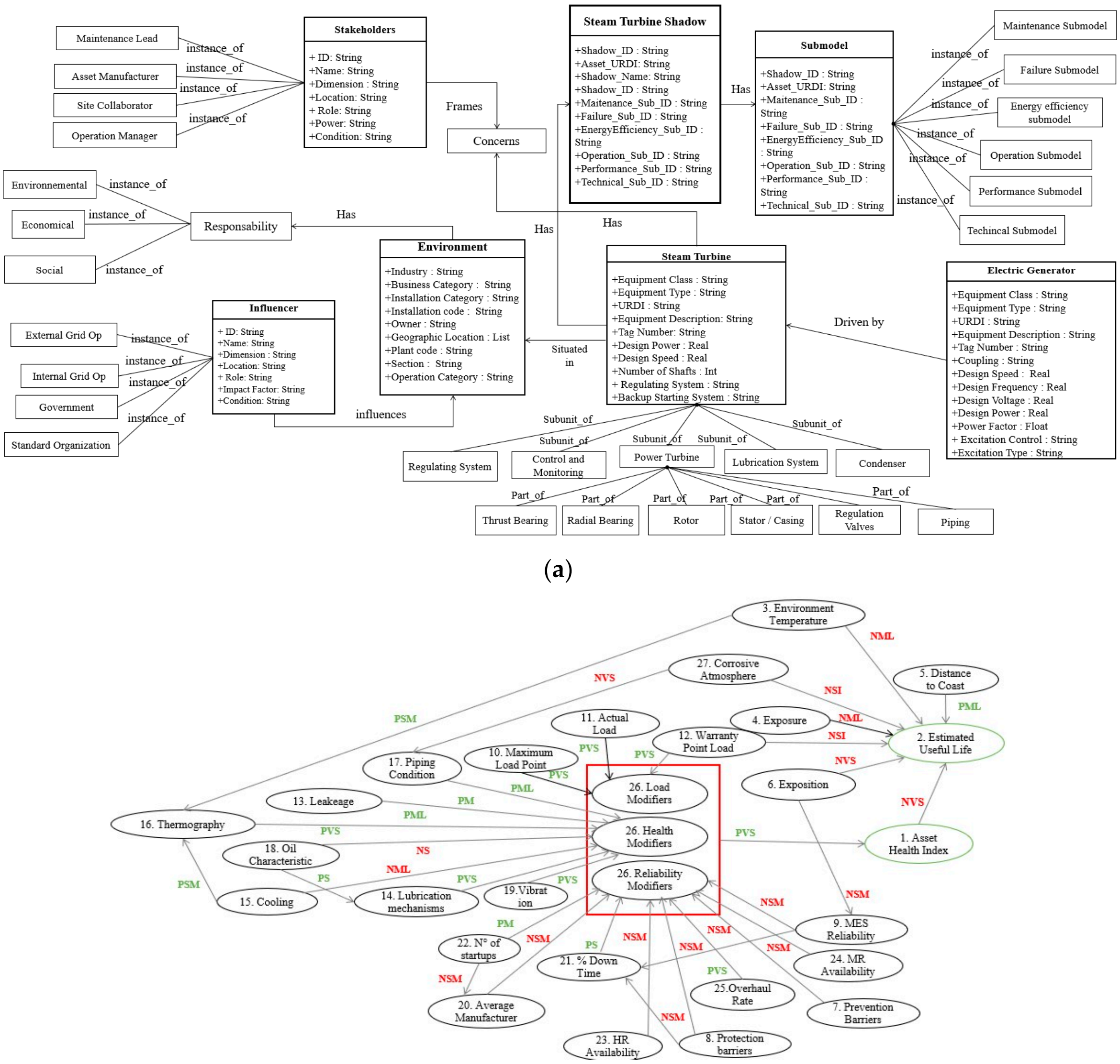


Figure 4. HT OMASE information view example for the use case—goal–role–capability model.



(**a**) (**b**)

Figure 5. HT OMASE environment view for the use case—domain model for steam turbine according to modified system boundaries by ISO (**a**). Cognitive map for health index definition (**b**).

4. Hybrid Twin Architecture Proof of Concept for TPP Digital Twin

This part aims illustrates the potential of our proposed HT-OMASE architecture for dealing with the presented business concerns in the case of TPP.

4.1. TPP Digital Twin Virtual Environment (BC1)

DT virtual environment and real plant dynamic behavior are described in this part.

4.1.1. Steam Turbine Modeling

A set of first modeling assumptions were considered for steam turbine modeling and simulation:

- A1. The steam expansion process in the turbine is supposed to be an ideal adiabatic and isentropic expansion.
- A2. Water steam expanded through turbine sections is supposed to comply with ideal gas pressure and temperature law.
- A3. Turbine efficiency at HP section is considered constant.

For the purpose of this paper, we put the focus mainly on steam pressure, temperature, enthalpy, and flow rate. The model of steam turbine sections gives in output discharge flow rate, steam temperature, and pressure which results from the depression at the level of turbine blades and from the evolution of the kinetic energy resulting from steam particles' velocity due to the acceleration transmitted by stage's wheels. Throughout this part, we have based our model on the modified Ellipse law for steam engines with a polynomial extension, material, and energy balances between the inputs and outputs of each system according to Equation (1) and thermodynamic fist principle represented by Equation (2).

$$\sum \dot{m}\ in = \sum \dot{m}\ out \tag{1}$$

$$Q - W = \sum \dot{m}\ outhout - \sum \dot{m}\ in\ hin \tag{2}$$

The relationship between inlet and outlet pressures are estimated from the operating data of the turbine according to multiple linear regression models using models input for estimation of output thermodynamic conditions according to Equation (3) by support vector regression (SVR). Temperatures at the outlet of each section *Tout* are calculated from the relation of perfect gases Equation (4) between turbine according to the pressures *pin* and temperatures *Tin* at the inlet, isentropic coefficient depend on pressures and temperatures of input in its turn K. The flow rate at the outlet of the section $\dot{m}\ out$ is estimated by Equation (5) deduced from the variation of mass for a given volume through time and geometric characteristics of sections. The enthalpy at each stage depends on the variations of the thermodynamic parameters at the sections and the inlet and outlet flow rates according to and will be detailed in the next part. Table 3 represents developed models for ST sections.

$$yi = \sum_{1}^{N} (a_i - a_i^*).\langle x_{i,}, x \rangle + b \tag{3}$$

$$T_{out} \ = \left(\frac{p_{out}}{p_{in}} \right)^{\frac{K-1}{K}} T_{in} \tag{4}$$

$$\dot{m}_{in} - \dot{m}_{out} = \left(\frac{p_{nominale}}{\dot{m}_{nominale}} \times V \times \frac{\partial \varphi}{\partial P} \right) \frac{d\dot{m}_{out}}{dt} \tag{5}$$

Table 3. Steam turbine sections models based on turbine design data.

	Pressure Models	Temperature Models	Flow Rate Models
Admission Model	$\frac{p_{roue}}{p_{admission}} = \frac{0.430}{1+0.4s}$	$\frac{T_{roue}}{T_{admission}} = \frac{0.782}{1+0.4s}$	$\frac{\dot{m}_{roue}}{\dot{m}_{admission}} = \frac{0.77}{1+5.15s}$
HP Section	$\frac{p_{extraction}}{p_{roue}} = \frac{0.186}{1+0.3s}$	$\frac{T_{extraction}}{T_{roue}} = \frac{0.544}{1+0.3s}$	$\frac{\dot{m}_{extraction}}{\dot{m}_{roue}} = \frac{0.454}{1+0.3s}$
IP Section	$\frac{p_{soutiarge2}}{p_{extraction}} = \frac{0.153}{1+0.7s}$	$\frac{T_{soutiarge2}}{T_{extraction}} = \frac{0.376}{1+0.7s}$	$\frac{\dot{m}_{soutiarge1}}{\dot{m}_{roue}} = \frac{0.168}{1+0.7s}$
IP-BP Section	$\frac{p_{soutiarage1}}{p_{CO}} = \frac{0.153}{1+1.4s}$	$\frac{T_{soutiarage1}}{T_{CO}} = \frac{0.376}{1+1.4s}$	$\frac{\dot{m}_{co}}{\dot{m}_{roue}} = \frac{0.378}{1+1.4s}$
BP1	$\frac{p_{soutirage2}}{p_{soutirage1}} = \frac{0.229}{1+1.5s}$	$\frac{T_{soutirage2}}{T_{soutirage1}} = \frac{0.535}{1+1.5s}$	$\frac{\dot{m}_{soutirage2}}{\dot{m}_{CO}} = \frac{0.70}{1+1.5s}$
BP2	$\frac{p_{echapement}}{p_{soutirage1}} = \frac{0.129}{1+1.9s}$	$\frac{T_{echapement}}{T_{soutirage1}} = \frac{0.4}{1+1.9s}$	$\frac{\dot{m}_{echapement}}{\dot{m}_{CO}} = \frac{0.30}{1+1.9s}$

Time constants for admission stage and IP-LP cross section were calculated according to stages geometric data.

$$p_{admission0} = 24.3 * 100 = 2430 \text{ KPa } \dot{m}_{admission0} = 41.56 \text{ kg/s}$$

$$V_{Etageadmission} = \pi \times h_{Etageadmission} \times r_{Etageadmission}{}^{2}$$

$$V_{Etageadmission} = 0.679 \text{ m}^3 \ \ \frac{\partial \varphi}{\partial P} (\ T_{admission0} = 498) = 0.133$$

$$\tau_{etage\ admission} = 5.15\ s$$

$$p_{soutirage1} = 1.61 * 100 = 161 \text{ KPa} \quad \dot{m}_{Soutirage1} = 2.46 \text{ kg/s}$$

$$V_{IP-BP} = 0.154 \text{ m}^3 \quad \frac{\partial \varphi}{\partial P}\left(T_{Soutirage1\_0} = 81\right) = 0.157$$

$$\tau_{IP-BP} = 1.4\ s$$

Control valve flow models that will be generalized for the five electrohydraulic valves instances in the system are represented by Equations (6)–(8) adapted from.

$$\dot{m}_{R1-R2-R3} = \dot{m}_{admission} \times ch_{valve}() \times \frac{p_{admission}}{59} \sqrt{\frac{(\pi_{adm})^{\frac{2}{\kappa}} - (\pi_{adm})^{\frac{\kappa+1}{\kappa}}}{0.0804}} \tag{6}$$

$$\dot{m}_{extraction} = \dot{m}_{roue} \times ch_{valve}() \times \frac{p_{roue}}{59} \sqrt{\frac{(\pi_{roue})^{\frac{2}{\kappa}} - (\pi_{roue})^{\frac{\kappa+1}{\kappa}}}{0.2217}} \tag{7}$$

$$\dot{m}_{soutirage1} = \dot{m}_{IP} \times ch_{valve}() \times \frac{p_{extraction}}{59} \sqrt{\frac{(\pi_{soutirage1})^{\frac{2}{\kappa}} - (\pi_{soutirage1})^{\frac{\kappa+1}{\kappa}}}{0.2869}} \tag{8}$$

In order to analyze the energy flows into and out of the turbine, we proceeded to the modeling of the different energy flows between the stages. This model is inspired by the IEEE configuration for steam turbines with condensation. The plant is characterized by three mechanical power components as presented through Equations (9) and (13).

$$P_m = P_{Turbine} - P_{losses} \tag{9}$$

$$P_{Turbine} = P_{HP} + P_{IP} + P_{LP} \tag{10}$$

$$F_{HP} = \frac{1}{1 + \frac{P_{IP}}{P_{HP}} + \frac{P_{LP}}{P_{HP}}} \tag{11}$$

$$F_{IP} = \frac{\frac{P_{LP}}{P_{HP}}}{1 + \frac{P_{IP}}{P_{HP}} + \frac{P_{LP}}{P_{HP}}} \tag{12}$$

$$F_{LP} = \frac{\frac{P_{IP}}{P_{HP}}}{1 + \frac{P_{IP}}{P_{HP}} + \frac{P_{LP}}{P_{HP}}} \tag{13}$$

The HP section receives the steam at the outlet of the inlet wheel which has undergone a first expansion and transmits it to the extraction valve which is connected to the LP network and to the superheater. Equations (14) and (15) present the ratio of power transmitted by the section to the shaft.

$$P_{HP} = \dot{m}_{Hp} \times \Delta h_{HP} \tag{14}$$

$$\Delta h_{HP} = \eta_{is-HP} \times \left(h_{roue} - h_{extraction,s}\right) \tag{15}$$

Equations (16) and (17) present power ratio transmitted by IP section to steam turbine shaft.

$$P_{IP} = \dot{m}_{IP} \times \Delta h_{IP} \tag{16}$$

$$\Delta h_{IP} = \eta_{is-IP} \times \left(h_{extraction} - h_{soutirage1,s}\right) \tag{17}$$

Equations (18) and (19) presents the ratio of LP power transmitted by the section to the shaft.

$$P_{LP} = \eta_{is-LP} \times A \tag{18}$$

$$\mathrm{A} = (\dot{m}_{CO} - \dot{m}_{soutirage1}) \times \left(h_{CO} - h_{soutirage2,s}\right) + (\dot{\mathrm{m}}_{\mathrm{CO}} - \dot{\mathrm{m}}_{\mathrm{soutirage1}} - \dot{\mathrm{m}}_{\mathrm{soutirage2}}) \times \left(\mathrm{h}_{\mathrm{soutirage2,s}} - \mathrm{h}_{echapement,s}\right) \tag{19}$$

4.1.2. Generator Modeling

The generator of the group is the part responsible for the production of electric energy through electrostatics. A typical representation of the alternator is adapted where this one receives a mechanical power transmitted by the rotation of the shaft of the turbine coupled to that of the alternator and thanks to this power as well as an excitation received by the network the alternator offers in output an electric power that is divided into active and reactive power. The parameters for the model definition are deduced from the characteristics extracted from design documents. The generator model is represented by Equations (20)–(27), respectively.

$$2\,H\,\frac{d\Delta\omega}{dt} = (T_m - T_e - D(w_0 - w)) \tag{20}$$

$$T_e = \frac{I \times U \times \sin(\delta)}{xw} \tag{21}$$

$$D_\omega = \xi \times \sqrt{\frac{\omega_s \times J_\Delta \times P_{max}}{2}} \tag{22}$$

$$T_m = \frac{P_m}{\omega} \tag{23}$$

$$Q = UI\ \sin\theta \tag{24}$$

$$P = UI\ \cos\theta \tag{25}$$

$$x = L\,\omega \tag{26}$$

$$H = \frac{\frac{1}{2}J_\Delta {w_0}^2}{100} \tag{27}$$

The exhaust steam from the steam turbine is condensed in a main condenser body by the cooling water flowing through the tubes. The cooling water flow rate is maintained at a constant value by a proportional integrator derivate (PID) controller. The return water temperature varies as well as the pressure inside the condenser. The constant condenser parameters are estimated by the manufacturer's data and approximated by historical data from the actual plant. The dynamic model of the steam condenser is based on the energy and mass balance of water. The steam pressure, heat transfer and condensate water temperature are represented by Equations (28)–(30), respectively.

$$\frac{dp}{dt} = \left(\dot{m}^{Exhaust_{steam}} - \dot{m}^{Condensate}\right) \times \frac{T^{condensate} \times R}{V^{Condenser}} \tag{28}$$

$$Q = UA\,\frac{T^{out\_water} - T^{in\_water}}{ln(\frac{T^{condensate} - T^{in\_water}}{T^{condensate} - T^{out\_water}})} \tag{29}$$

$$\frac{dT}{dt} = \frac{Q}{M^{water} \times C_p} + \frac{\dot{m}^{water}}{M^{water}} \times \left(\, T^{out\_water} - T^{in\_water}\right) \tag{30}$$

4.2. DT Agents' Development and Implementation

4.2.1. Agent Class Model

Our development perspective consists in implementing an Observe Orient Decide and Act (OODA) loop through the collaboration between a set of intelligent and autonomous agents. The function of the loop aims to cover the main building block of the condition monitoring system as defined by ISO 13374:2015 standard [71] presented in Figure 6.

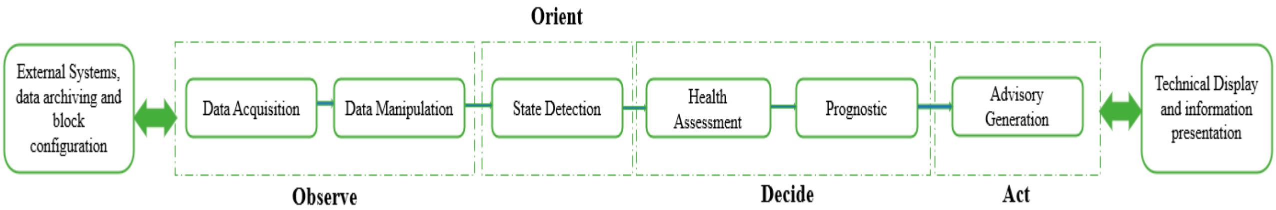


Figure 6. ISO 13374:2015 through OODA loop.

For this purpose, we have defined a list of roles and capabilities. These different roles are assigned to a pool of six agents. The mission of each agent is to perform one of the four functions defined by the loop. The collaboration amongst agents ensures that all functions are linked to the previously defined core objective of the organization. Figure 7 represents the agent society view of the DT-OMASE system. The first agent of the loop is the mediator agent that is responsible for the initiation of the loop through environment observations extraction and analysis for behavioral mapping and real twin health status evaluation. In order to fulfill his assigned functions within the loop of observation and orientation and his attributed goal of first-level field interrogation mediator agent is provided with communication interfaces and protocols that enable it to interact with system users and physical twins' interpreters as well as other agents of the system.

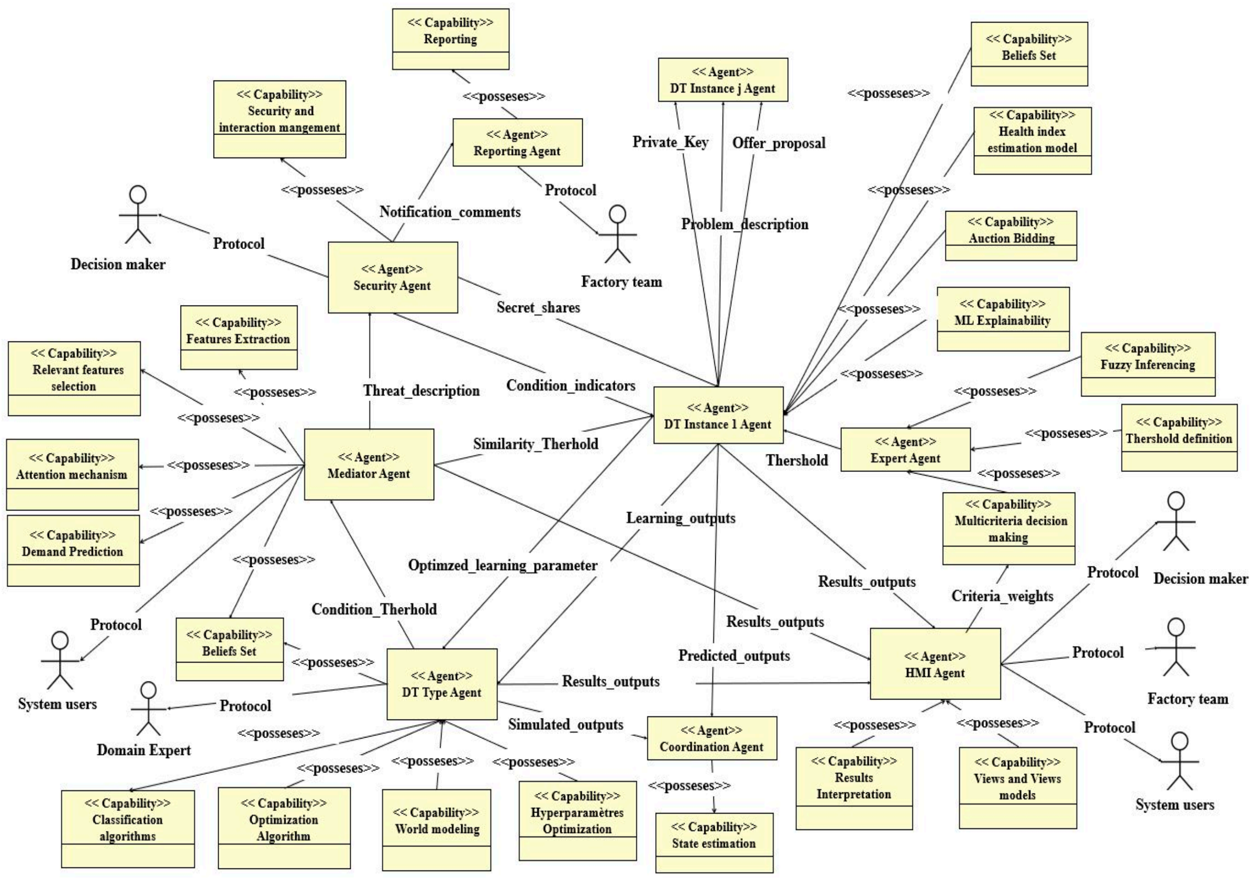


Figure 7. HT OMASE society view for the use case—agent class model.

Agent Internal Structure: Under our framework, each network consists of a set of offline and online twins that act individually to achieve their respective goals and collectively to emerge with a strategy that responds perfectly to changes in their dynamic physical environment. Each network governs a group behavior modeled by a joint action on the environment and to each action, the environment responds with a reward that evaluates the effectiveness of the group strategy implemented by DT in response to changes in its state. This continuous exchange with the environment allows the twins to learn from their group experience but also from each other's experiences with reference to their internal group strategy but also taking into account the strategy deployed by the neighboring network. Two groups of reactive and hybrid digital twins constitute the networks; we define them as DT-types and DT-instances., it introduces the development scheme of these two agents in reference to the basic model proposed for hybrid and cognitive agents in a MAS context.

4.2.2. Plan and Protocol Models for HT-OMASE Agents

This part details the architecture agent's workflows and realization. In order to apprehend agents' performances with regards to the defined problematics real data from the physical twin automation system archive were extracted. The extracted data set consists of TPP main components and 13 condition-checking parameter inputs for three months from 3 March 2021 to 10 May 2021 with an extraction frequency of 1 min, the chosen time frame covers all three states of the system's operation no loading start, ramp up, and steady state. Table 4 describes the input dataset.

Table 4. Input dataset description.

Symbol	Description	Unit
	Inputs	
Fad	Admission Flow	t/h
Tad	Admission Temperature	°C
Pad	Admission Pression	bar
	Outputs	
Proue	Admission wheel pressure	bar
Pex	First steam extraction pressure	bar
Fex	First steam extraction flow	t/h
Pa1	Steam extraction 1 pression	bar
Fa1	Steam extraction 1 flow	t/h
Pa2	Steam extraction 2 pressure	bar
Fa2	Steam extraction 2 flow	t/h
Pech	Exhaust steam pressure	bar
Tech	Exhaust steam temperature	°C
VHP-x	HP shaft vibration X	µm
VHP-y	High pressure (HP) shaft vibration Y	µm
VLP-x	Low pressure (LP) shaft vibration X	µm
VLP-y	LP shaft vibration Y	µm
Tspeed	Steam turbine speed	rpm
PTurbine	Steam turbine generated power	MW
Pa	Generator active power	MW
F	Generator frequency	Hz
Pr	Generator reactive power	MW
Papp	Generator apparent power	MW

- **Mediator Agent (RQ2.2)** The observe function of the OODA loop is entrusted to mediator agents whose role consists in observing the physical environment and its digital and physical agents, collecting sightings of physical twins, analyzing them, and transmitting to upper layer decision-makers permanent conditions indicators required for assets behavioral analysis within the virtual environment. In order to achieve their assigned roles, mediator agents are provided with a set of capabilities mainly features extraction and selection, and load forecasting. Features selection and extraction are executed by mediator agents concurrently, and outputs from it are exploited for condition indicators computing and anomaly detection. Received stream data according to a defined window are transmitted to mediator agents by communication interfaces with physical twin data sources according to a Foundation for Intelligent Physical Agents (FIPA) based subscribe interaction model represented in Figure 8.

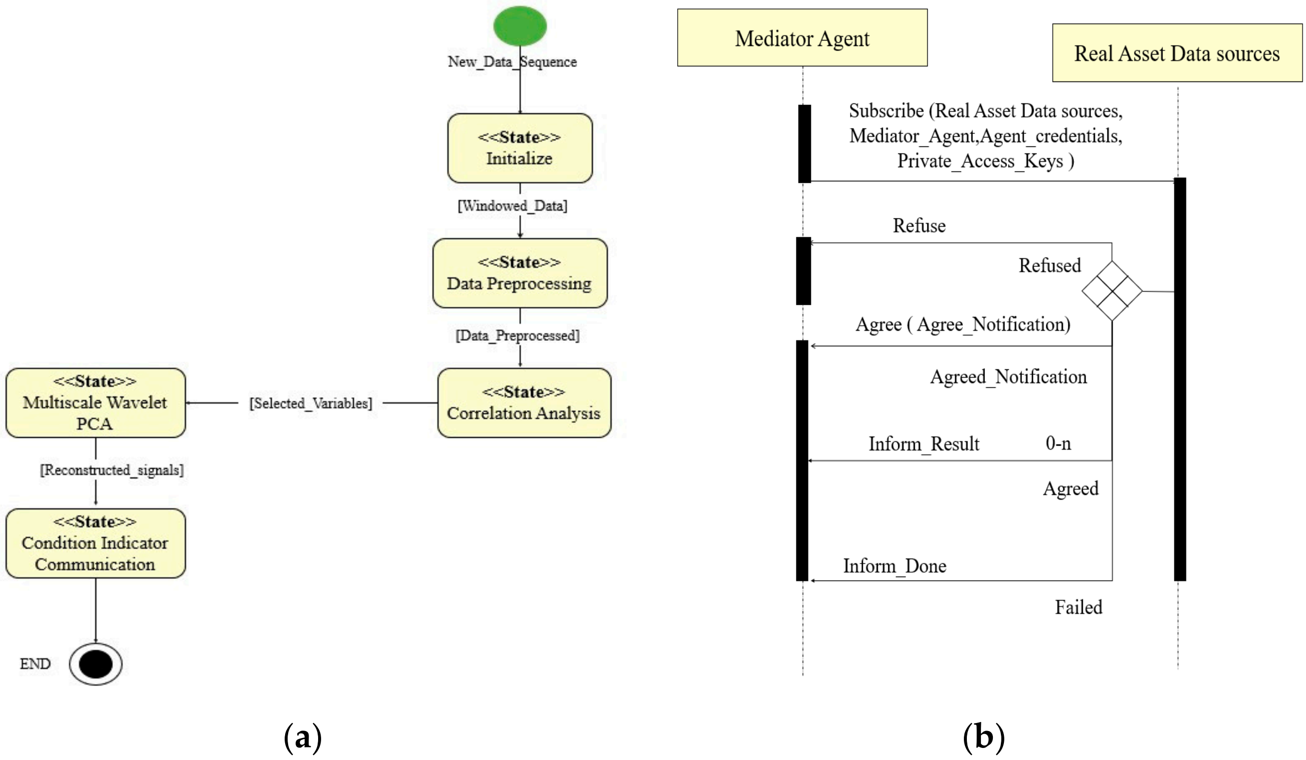


Figure 8. Plan model for features extraction and selection capabilities (**a**). Protocol model for mediator agent and physical twin interaction (**b**).

The first step consists of data preprocessing and filtering for data cleaning, missing values imputation, and correlation analysis. Linear interpolation is used for missing values filling according to Equation (31) and the Pearson coefficient is calculated in order to estimate dependencies between input and output parameters according to Equation (32). Linear interpolation estimates the unknown value $\hat{y}$ in the same increasing order as previous values of x and y.

$$\hat{y}(x) = y_i + \frac{(y_{i+1} - y_i)(x - x_i)}{(x_{i+1} - x_i)} \tag{31}$$

$$\rho(x,y) = \frac{COV(x,y)}{\sigma_x \sigma_y} \tag{32}$$

The preprocessed data sequence is then transmitted to feature extraction and selection processes that are executed concurrently by discrete wavelet transform and dimensionality reduction by principal component analysis through multiscale principal component analysis (MPCA) according to Equation (33).

$$WX = (WT)\ P^T \tag{33}$$

MPCA is used in order to ensure proper data are fed to DT instances for anomaly detection and to avoid false positive alarms. Each variable in the raw data set is decomposed into different wavelets according to the orthonormal wavelet. W is the orthonormal matrix, representing the orthonormal wavelet transformation operator containing the filter coefficients. Components are selected based on a defined threshold and the retained ones go to inverse wavelet transform for preprocessed signals reconstruction.

The last capability of mediator agents as strategic watchers of the external environment. It consists of demand side management through load forecasting. Figure 9 introduces the capability model for demand forecasting.

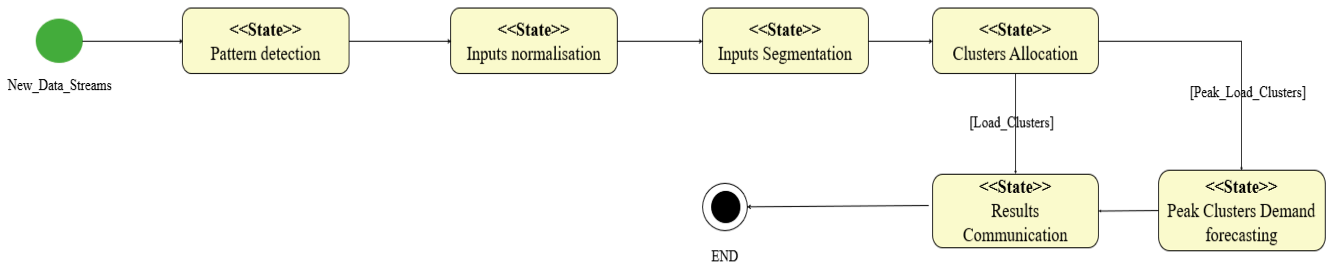


Figure 9. Plan model for load forecasting.

As mentioned in the introduction, the TPP discussed supplies of electricity and medium steam to value creation processes, and demand fluctuations have to be managed in order to monitor off-design conditions. Mediator agents support the fulfillment of the 1.1 subgoals and help in dealing with RQ 2.2 Demand forecasting results are communicated to DT Types for control command scenarios simulation and testing.

- **DT Instance Agent**

DT instances agents receive outputs of mediator agents' analysis and according to it decides on physical twin health state and performances required by BC3. Its decision mechanism is composed of a set of capabilities mainly a degradation model for health status estimation, auction bidding for collaborative prognostics, and interpretation algorithms for model results. Explainability and root cause analysis is defined by RQ 3.4. In addition to these main capabilities constituting decision-making and learning mechanisms, DT instances agents are provided with communication interfaces that enable them to interact with instances networks, mediators, types of networks, the physical environment, and its users in conformance with RQ 4.4. Figure 10a–c, respectively, introduces a protocol model for sealed auction bidding, a protocol model for communication with mediator agents, and a capability model for case-based reasoning.

Anomaly detection consists of two main blocks. Instances receive data directly from mediator agents for anomaly detection and evaluate it according to the Isolation Forest IF algorithm. The fused anomaly score is formed through aggregation of IF anomaly scores represented by Equation (34) for each defined health modifier.

$$s(x,n) = 2^{-\frac{E\ (h(x))}{c(n)}} \quad (34)$$

Attributes of weights are computed according to a game theory approach and Shapley values according to Equation (35). Attributes weights are communicated by the interpretability mechanism. Based on results obtained from this analysis, they are communicated to decision-makers and field collaborators by agents' communication interface with Human Machine Interface (HMI) agents.

$$\Phi_i(v) = \frac{1}{|N|!}\sum_R [v(P_i^R \bigcup\{i\} - v\left(P_i^R\right)] \quad (35)$$

The weights of attributes are communicated through interpretability mechanism that analyzes anomaly detection capability out- put to assign contribution of each attribute to the final estimated health status of assets. Health status prediction is based on a MPCA-LSTM Long Short-Term Memory architecture that takes as inputs anomaly detection communicated by mediator agents.

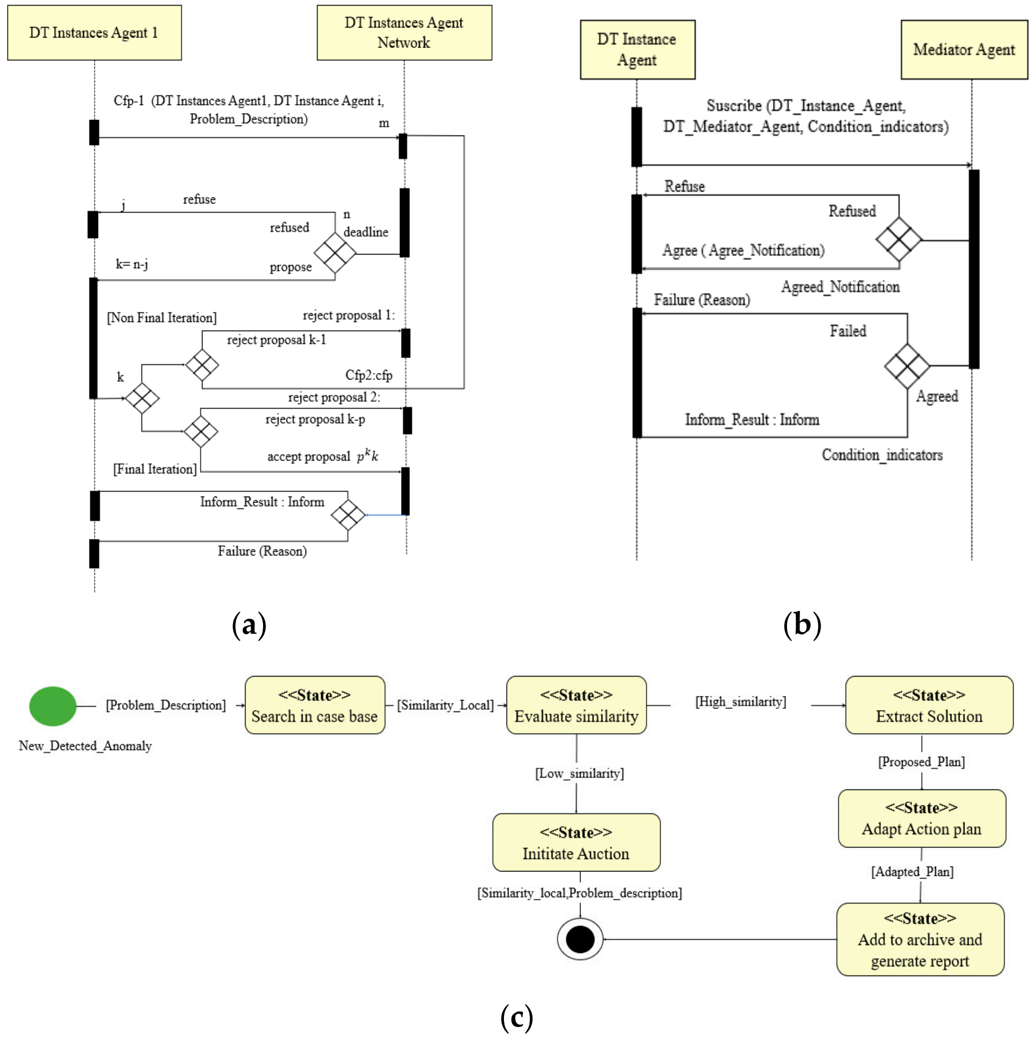


Figure 10. Protocol model for auction bidding among instances (**a**). Protocol model for instances and mediators' communication of observations (**b**). Plan model for case-based reasoning (**c**).

The auction process is based on Iterated Contract Net Protocol, and it consists of initiating a call for proposal for collaborative prognostics amongst instances of the same type. Proposals are evaluated according to similarities of problem description cases within DT instances case bases of maintenance record and costs of adaptability of the solution to the specific concerned instance context. The weights of attributes for similarity evaluation is introduced to the process of proposal.

The results of health states are exploited for control action optimization by DT instances, which take in addition to health state prediction, input thermodynamic conditions of steam and power demand forecasting in order to control steam turbine valves openings.

- **DT Type Agents**

DT type learning models are communicated to DT instances for training and retransmitted after for further optimization of models hyperparameters. DT type agents receives prediction outputs of mediators as well and accordingly enables to test different response strategies that can be tested and validated within the virtual environment of DT types. Figure 11 represents a protocol model for learning hyperparameters optimization.

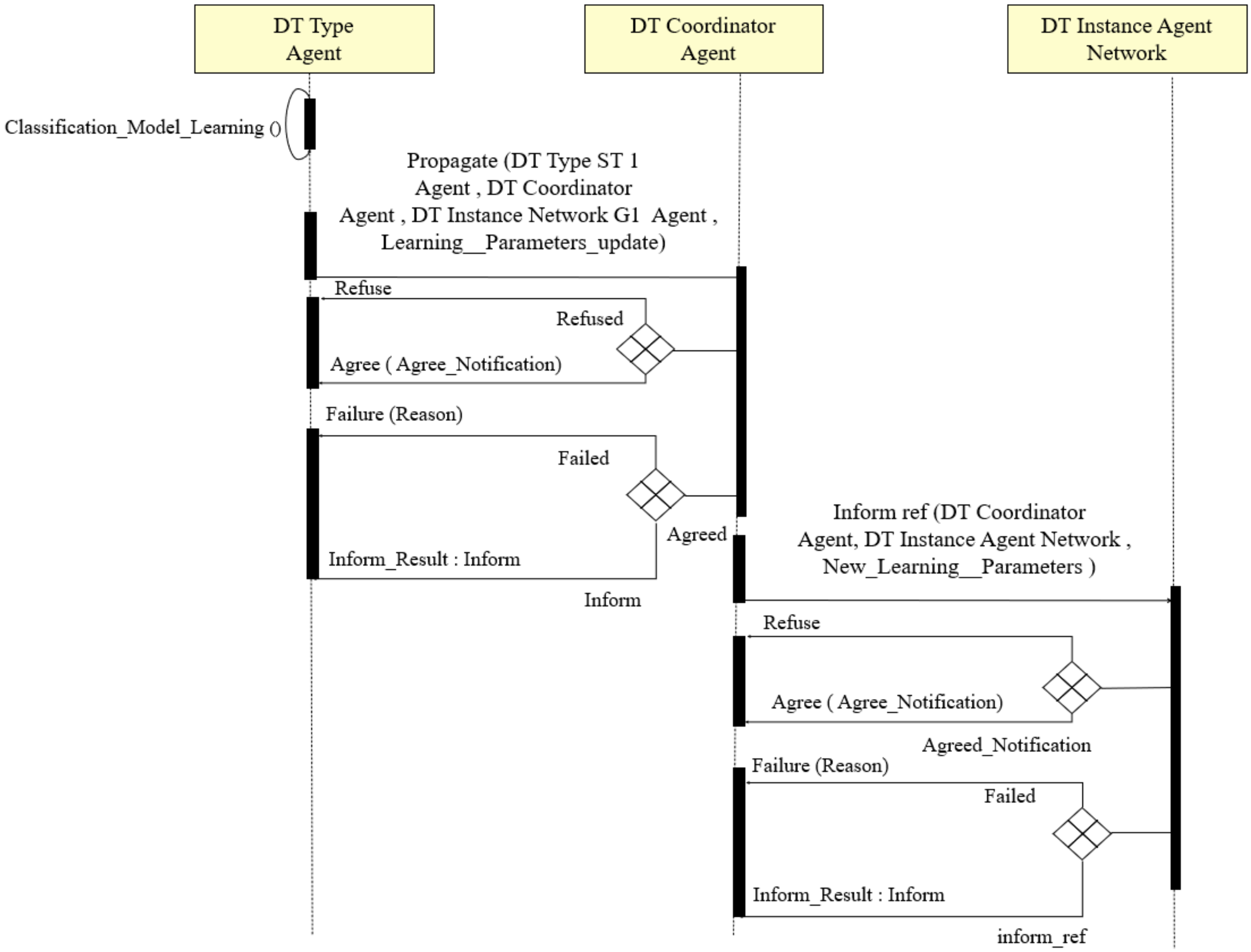


Figure 11. Protocol model for learning hyperparameters optimization.

DT type agents, based on their interactions with the virtual environment, develop a classification model that is communicated through coordinator agent to DT instance agents that tests the model and retransmit their learned parameters to coordinators for aggregation and optimization. DT types virtual environments and behaviors, which are developed through MATLAB/Simulink types, help in control scenarios definition, testing, and validation in the case of failures and instances case bases enrichment. For synthetic data generation, three basic failure modes are simulated, abnormal instrument reading, fail to start, and erratic output. The mutual impacts of these failure modes on the structural deficiency failure mode are analyzed for the three components. Failure modes are selected according to ISO 14224: 2016 and Pareto analysis of the failure history of the studied plant. A set of characteristics are defined for fault simulation mainly start and stop injection times, intensity, and frequency. Generated data are exploited by DT agents for further analysis as discussed in the paper. National grid disturbances impact simulations are considered as well in fault simulation for steam turbine generators.

- **HMI Agent**

Human machine interface (HMI) agent works as an ergonomic middleware with DT human users. Results are presented to users depending on their interests and concerns according to a set of views and views models that constitute the beliefs of HMI agents. The decision mechanism of HMI agents consists of a controller unit that enables it to update, modify, and adapt views. Different views are developed and fed by virtual environment outputs and DT type agents' analysis.

- **Expert Agent**

This agent acts as a knowledge capitalization unit for the architecture; it combines both the results of the architecture and the preferences communicated by the users and stakeholders of both instance and type agents. It is assigned the role of knowledge representation and attributed fuzzy inferencing and multicriteria making capabilities. These capabilities are exploited by expert agent in order to assist DT agents in their missions. Multicriteria decision-making results are communicated to DT instances in order to update their case base repositories of maintenance records through a reputation mechanism, where cases as well as their proposed action plans are evaluated prior to their deployment by expert agent and attributed a reputation score that enables agents to keep upgraded about the most efficient maintenance policies for future encountered problems, and to enhance auction bidding processes among DT instances agents. The weights of criteria for multicriteria decision-making are communicated by decision makers through HMI agents. This part will be detailed in future works.

- **Security Agent**

In the context of this paper, security agents intervene in the auction process among DT instances in order to ensure secure interaction for knowledge exchange. The auction process between auctioneer DT instances and selected bidders is achieved by the establishment of a smart contract. Contract requirements are defined by the DT instance bidder and its related owners and stakeholders. Once requirements are validated by DT instances and at least one involved stakeholder in the process, the DT auctioneer is provided with a private key in order to access to the concerned case base report. Private key construction is insured by the security agent through the Shamir secret key sharing scheme, two secret shares are provided by the bidder, and the remaining share is communicated by DT Instance auctioneer.

5. Experimental Results

In this section, simulation results of a first prototype for the proposed agents and their interactions with the developed virtual environment in MATLAB Simulink are presented. The DT-OMASE architecture undergoes two stages. The first one is the online stage, where the developed DT instances agents, with the help of mediator agents, analyzes the current state of the system and tries to detect deviations from the normal behavior in real time. The second stage is the offline stage, which consists first of the virtual environment that serves as a testing interface for different scenarios developed by the user and learned by the agents, and secondly, it serves as an optimization tool in order to improve agent proactivity and learning capacities by the interaction with DT types. Agents are developed in python. Communication with the physical twin is established through a communication (COM) interface developed with Python, and consists of sending specific requests to PT data sources and distributed control system archives. Agents' analysis results are stored in a database and imported into the virtual environment through a dedicated script developed in MATLAB. Communication amongst agents within the architecture is established through the Python framework for multiagent systems. Communication with the environment in scenarios testing is enabled by the MATLAB engine for Python.

Three basic tests are defined combining both normal and abnormal conditions. The main purpose of these tests is to address the defined concerns by system stakeholders and evaluate agents' individual capabilities and coordination in order to solve encountered problems within the physical environment.

5.1. Testing Scenario 1: Anomaly Detection and Root Causes Analysis for Steam Turbine (ST)

Figure 12 represents a correlation analysis of the signals and the different dependencies amongst steam turbine outputs. Figure 13 represents the mediator agent feature selection and extraction capability for Vibration HP-x, Vibration HP-y, Vibration LP-x and Vibration LP-x signals. A threshold of 0.3 was selected in order to ensure appropriate filtering without losing relevant information from the input signals. It can be seen from the figure that the filtered signals by MPCA exhibit the same trends as the original ones.

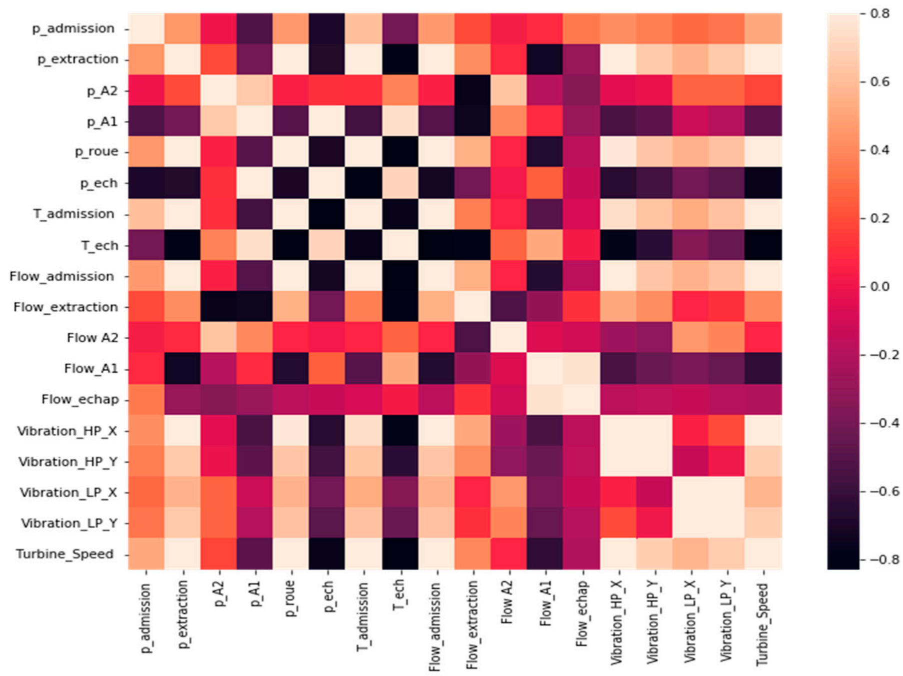


Figure 12. Correlation analysis of steam turbine parameters.

Reconstructed input vector of features through MPCA then is fed to the Isolation Forest (IF) for anomaly detection. Simulation results of produced anomaly scores and anomalies detection for different contamination rates are represented in Figure 14. For the training of the model, 70% of data samples are used for training and the remaining 30% of data samples are used for validation.

The results of this first part are used for health index prediction model training and testing. Different recurrent neural networks (RNN) models are compared, and the models' performance comparison results for steam turbine and generator operational condition in the selected period are represented in Table 5.

The interpretation of these results for root causes analysis are provided by the interpretability capability of DT instances. Figure 15 represents interpretation results for HI prediction and gives highlights on the different factors that contributed to the first registered anomaly.

Mutual dependencies and contributions between interacting factors are represented by different dependence plots. Analysis results are saved on reports for further investigation by users. It can be seen from the summary plot that the main factors that contributed to the first detected anomaly are pressure and admission flow. Figure 15 represents the global importance of the variables calculated by the shape values. Thanks to the fact that the values are calculated for each example of the dataset, it is possible to have additional information on the impact of the variable according to its value. For example, admission pressure, which is the most important variable, has a negative impact when the value of this variable is high.

5.2. Testing Scenario 2: TPP Steady State Dynamic Simulation

The XSteam Library in the MATLAB corresponding to IAPWS 97 Industrial Formulation 1997 for the Thermodynamic Properties of Water and Steam is used for approximation of enthalpy in both superheated 1 and subcooled 2 regions. Models testing and validation for the virtual environment are implemented in MATLAB/Simulink.

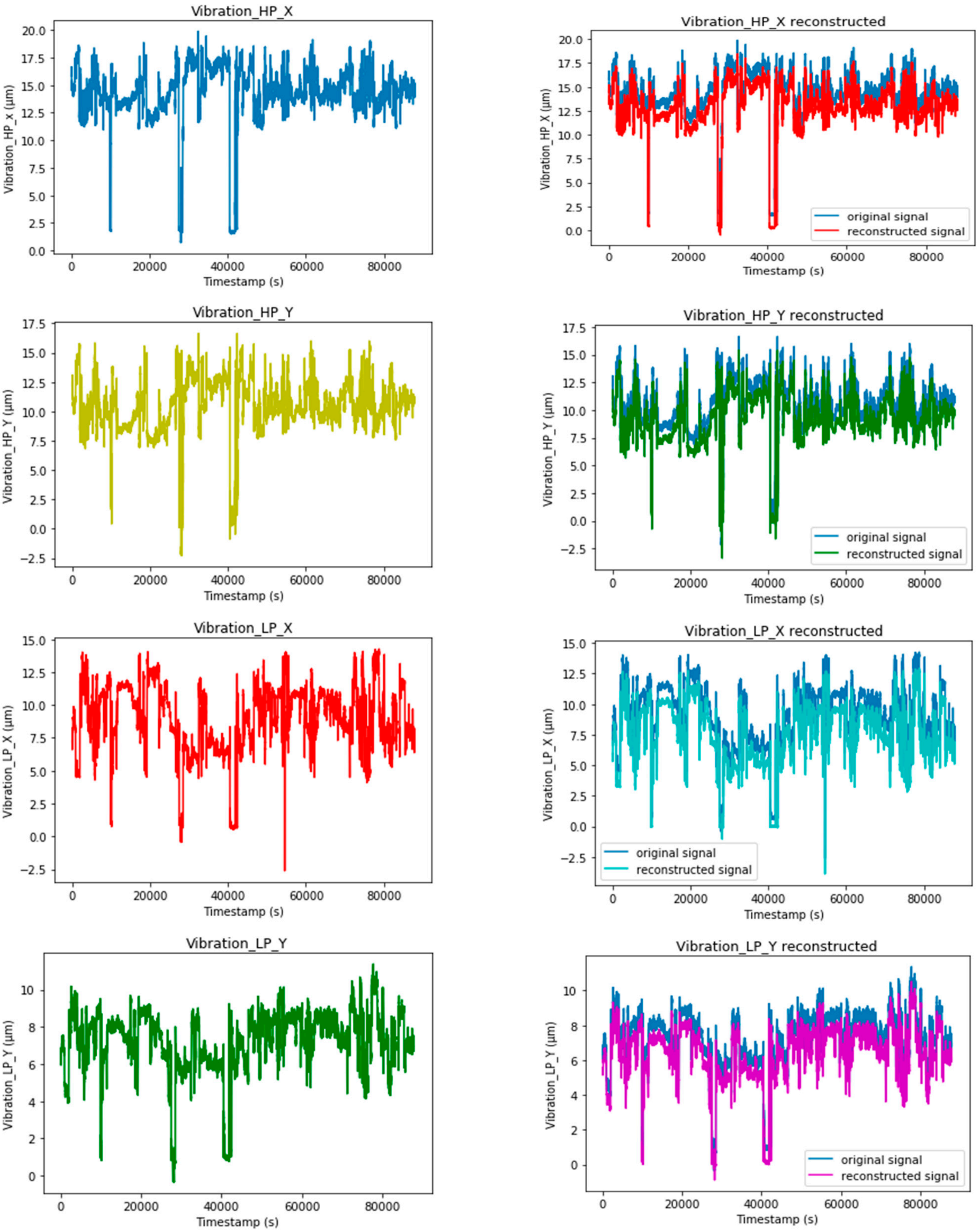


Figure 13. Oirginal signals vs. reconstructed signals by MPCA for Vibration HP_x, VibrationHP_y, VibrationLP_x, and and VibrationLP_y with a 0.3 threshold.

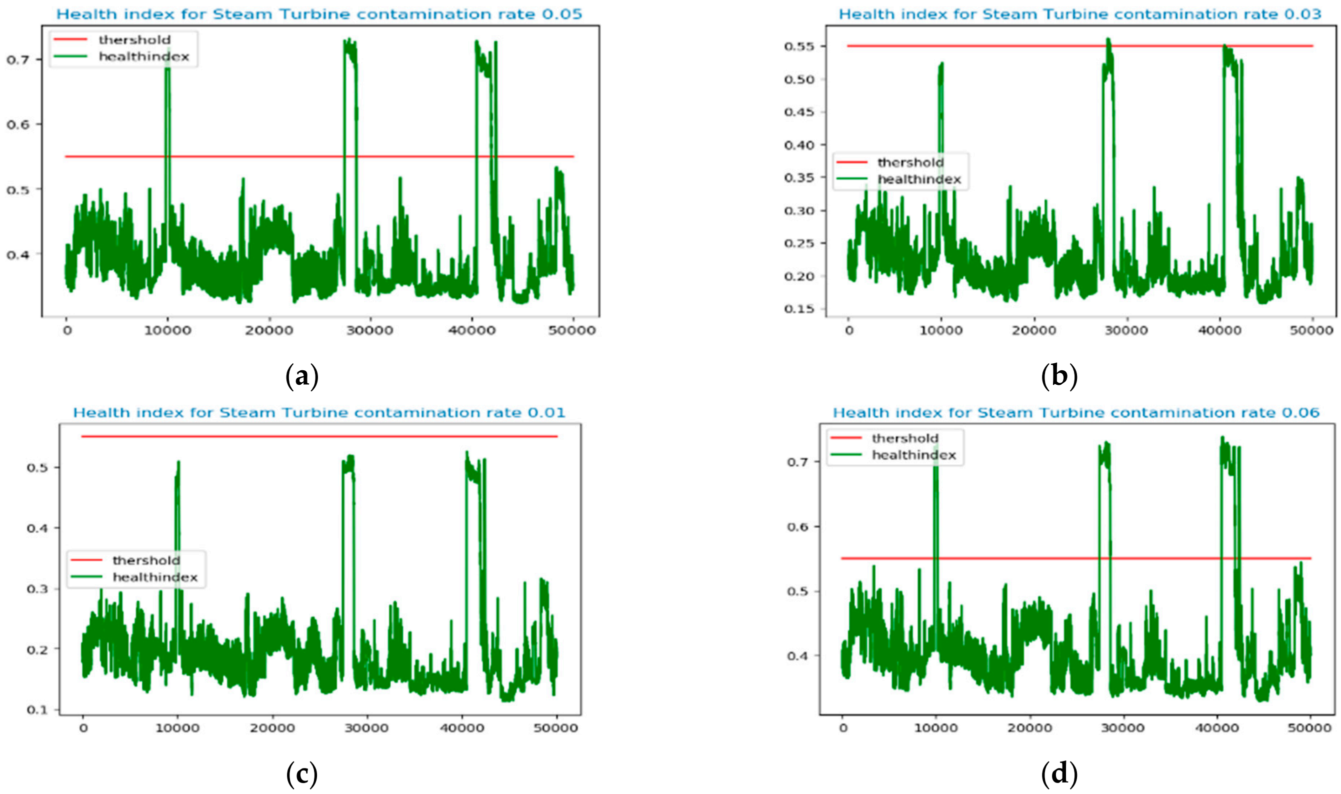


Figure 14. Health index for steam turbine through Isolation Forest with different contamination rates c = 0.05 (**a**); c = 0.03 (**b**); c = 0.01 (**c**); c = 0.06 (**d**).

Table 5. Steam turbine health index forecasting.

	MAE	RMSE	R2_Score	Execution Time (s)
MPCA-BI Bidirectional-LSTM-Attention	0.136	0.024	0.960	110
MPCA-LSTM-Attention	0.131	0.023	0.964	103
MPCA-LSTM	0.117	0.019	0.975	104
XGBoost-BILSTM	0.143	0.027	0.948	110
BILSTM	0.145	0.028	0.945	111
XGBoost-GRU	0.151	0.031	0.936	800
Variational Auto Encoder (VAE)-BILSTM	0.144	0.026	0.954	157
AE-LSTM	0.140	0.026	0.955	500

Figures 16–18 represents, respectively, simulation results for pressure, temperature, flowrate, turbine speed, and power against plants data for different operating conditions, loads, and control valve openings.

Simulation results are represented through Figure 19.

Simulation results for condenser model simulation and validation are represented by Figure 20.

Statistical metrics represented in Tables 6–8 are able to provide information on the overall performance of the developed models and their comparison with state-of-the-art proposed models.

Figure 21a,b represents, respectively, DT type views developed with MATLAB/App for the steam turbine simulation graphical user interfaces, performances, and fault simulation interfaces for synthetic data generation.

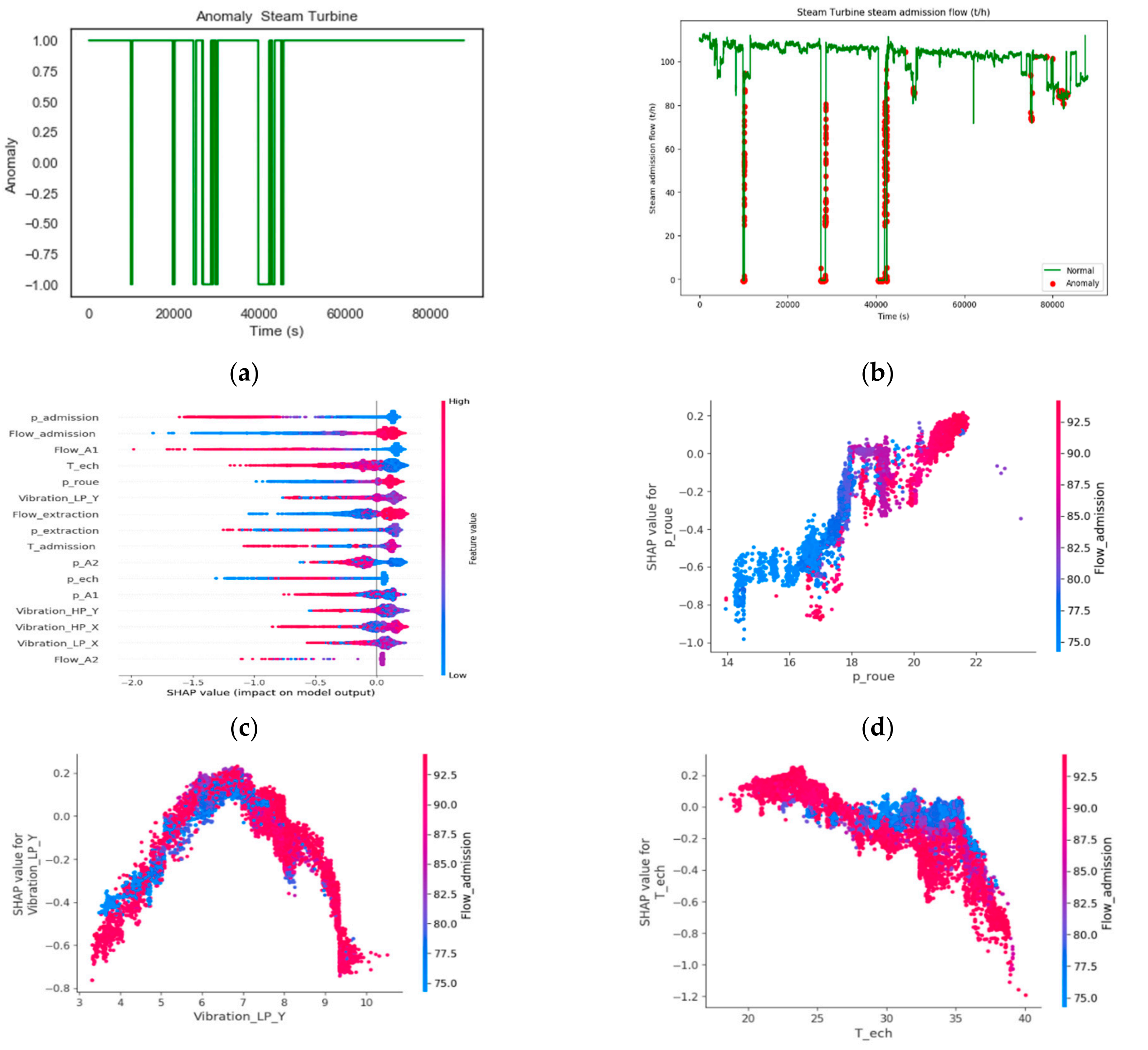


Figure 15. Anomaly forecasting according to IF for steam turbine. (**a**) Anomaly in steam turbine admission flow. (**b**) Summary plot for contribution to steam turbine detected anomalous point in testing data samples. (**c**) Dependence plot of admission wheel pressure. (**d**) Vibration LP (**e**) and exhaust temperature (**f**) on steam turbine health state and their mutual interaction with admission flow.

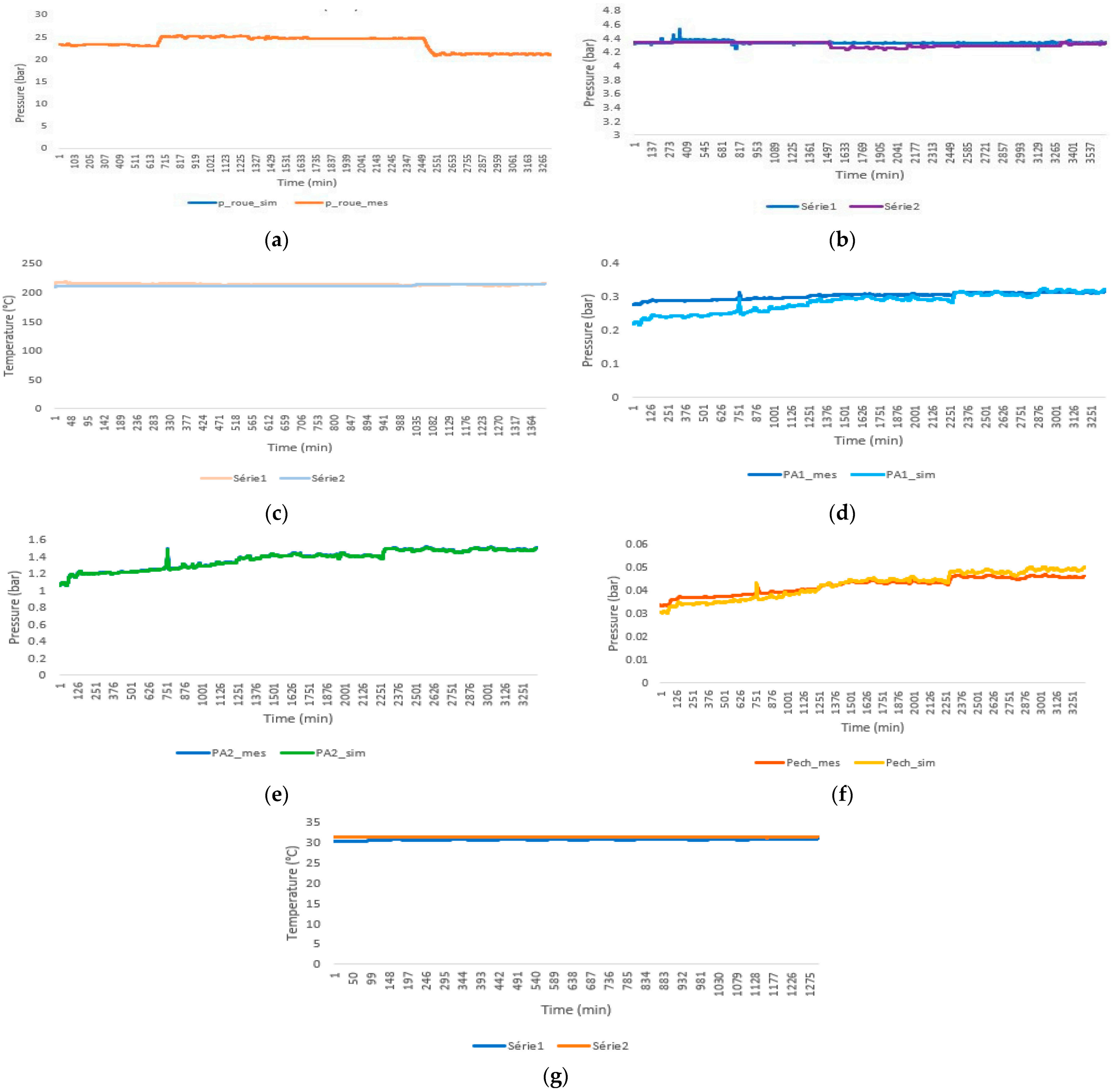


Figure 16. Admission stage pressure. (**a**) HP section pressure. (**b**) HP section temperature. (**c**) IP stage pressure. (**d**) LP stage pressure (**e**) exhaust pressure (**f**) and exhaust temperature (**g**) dynamic simulation.

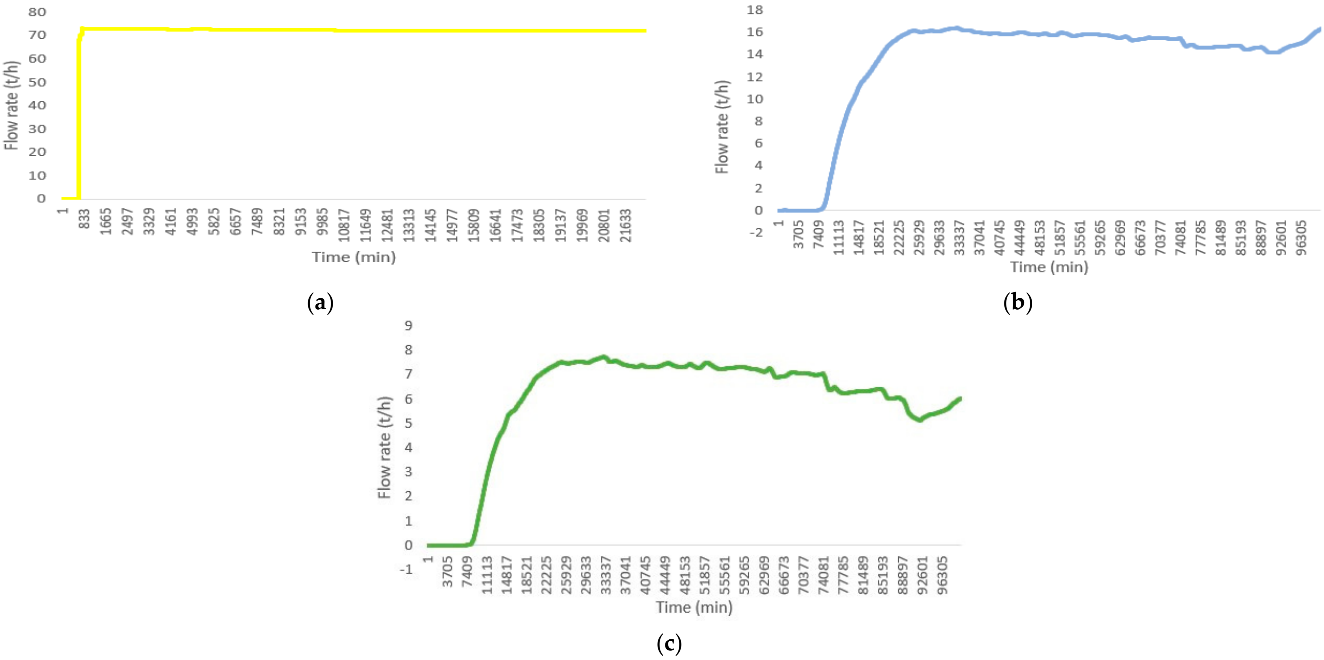


Figure 17. HP stage flow rate. (**a**) IP stage flow rate (**b**) exhaust flow rate (**c**) dynamic simulation.

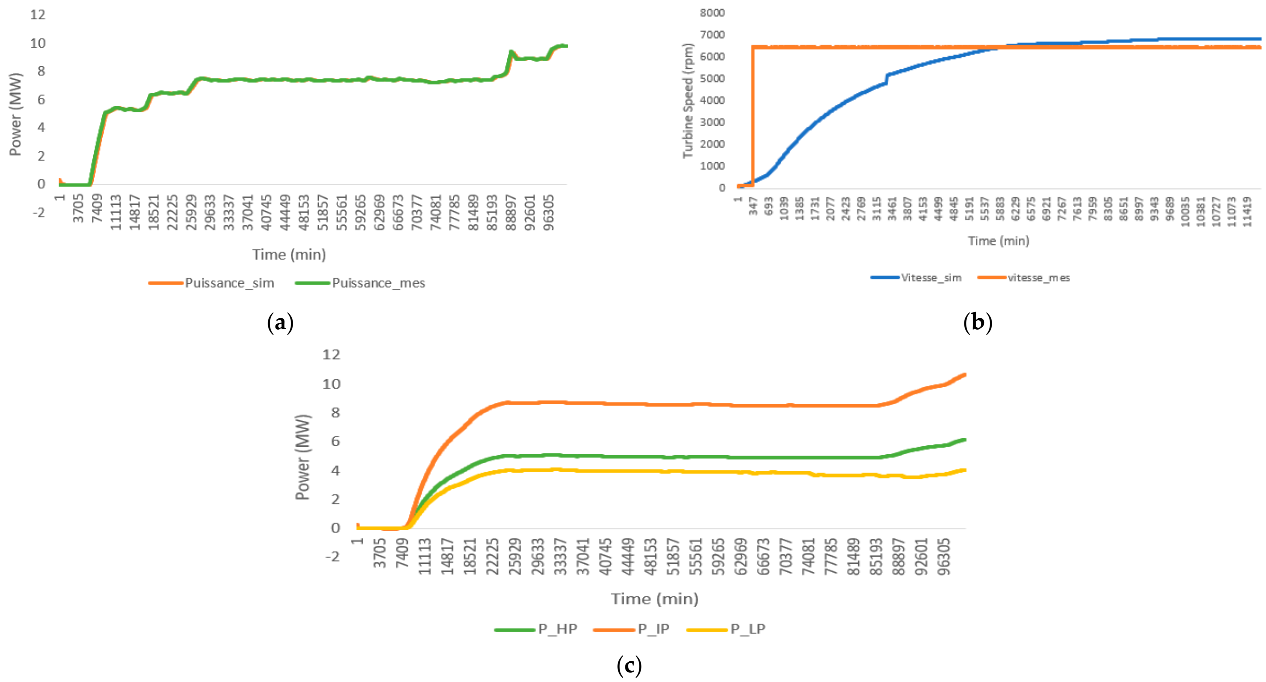


Figure 18. Steam turbine produced power. (**a**) Speed. (**b**) HP section produced power, IP section produced power, LP produced power (**c**).

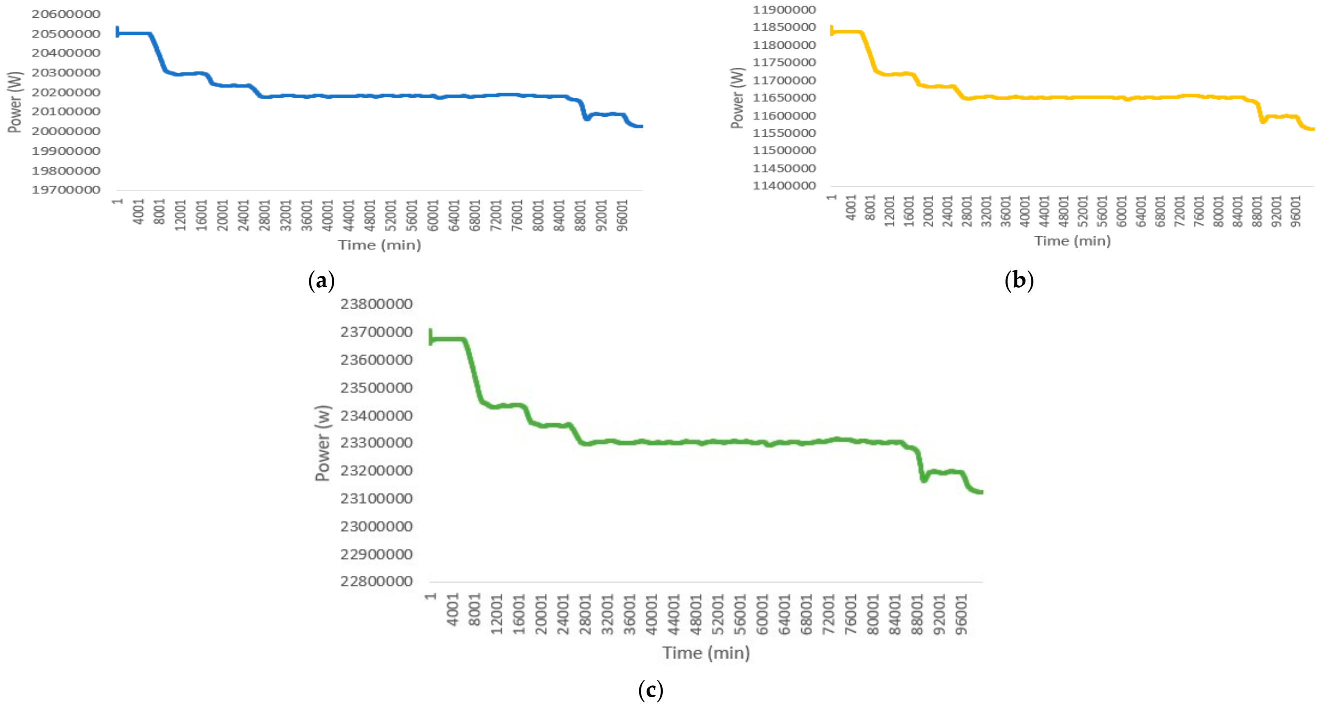


Figure 19. Generator active (**a**) reactive (**b**) and apparent power (**c**).

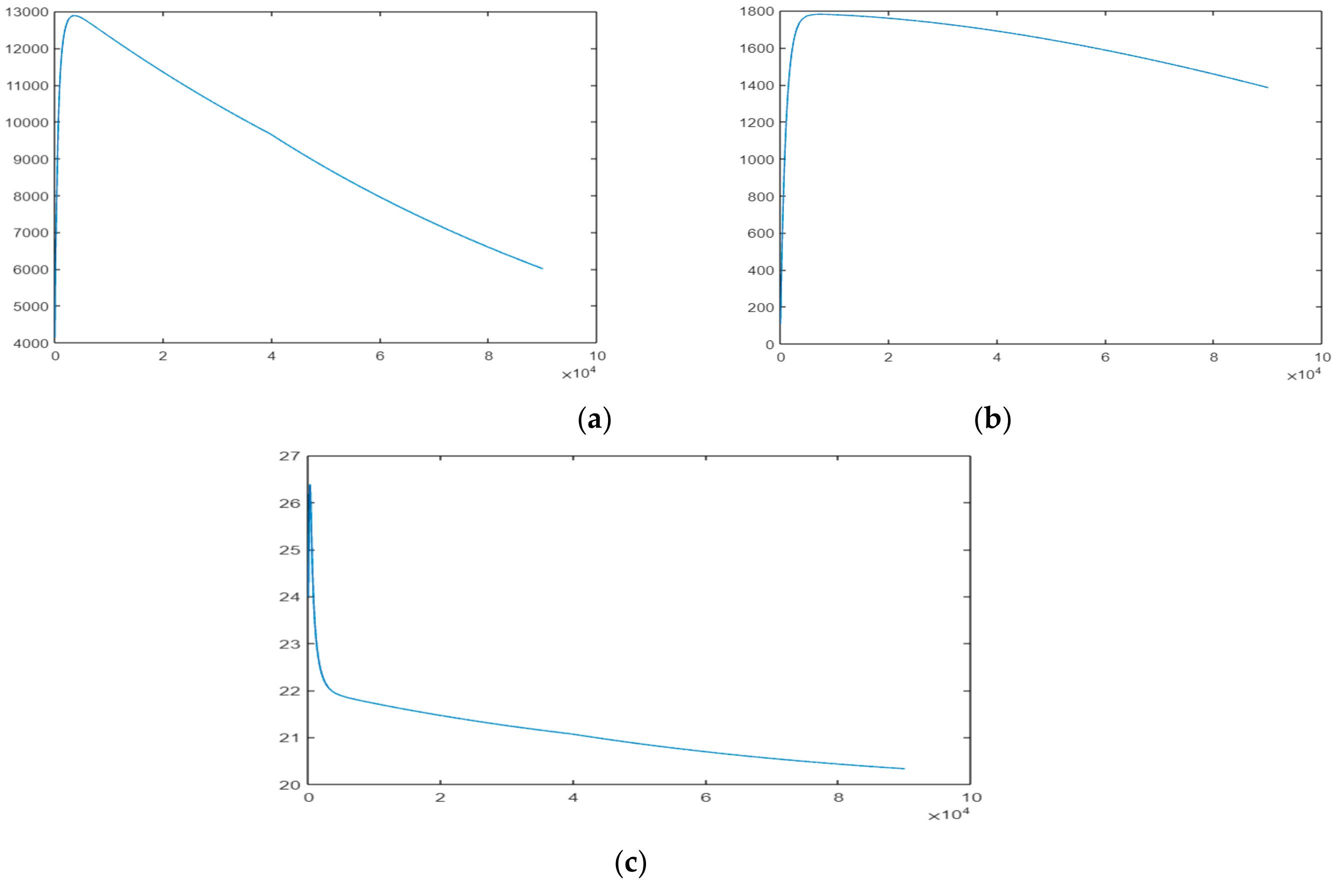


Figure 20. Simulation of condenser flow (**a**) heat (**b**) and cooling water temperature (**c**).

Table 6. Simulation results evaluation for condenser.

Parameters	MAD	MSE	RMSE	MAPE
Condenser Temperature	1.65×10^{-9}	7.12×10^{-13}	2.32×10^{-6}	9.36×10^{-5}
Condenser Pressure	5.30×10^{-6}	6.79×10^{-6}	0.004	2.86×10^{-5}

Table 7. Simulation results evaluation for generator.

Parameters	MAD	MSE	RMSE	MAPE
Active Power	0.00014	0.0001	0.0132	0.0032
Reactive Power	4.8412×10^{-5}	2.9477×10^{-5}	0.0111	0.0002
Apparent Power	4.8412×10^{-5}	2.9477×10^{-5}	0.0111	0.0002
Current L1	0.0144	4.2884	2.0497	0.0011
Current L2	0.0142	4.0556	2.0596	0.0011
Current L3	0.0144	4.2884	2.0497	0.0011
Voltage L1–L2	2.4039×10^{-5}	1.1400×10^{-5}	0.0033	0.0002
Voltage L2–L3	2.4386×10^{-5}	1.1655×10^{-5}	0.0034	0.0028

Table 8. Simulation results evaluation for steam turbine.

Parameters	MAD	MSE	RMSE	MAPE
Admission pressure	8.1217×10^{-7}	2.1625×10^{-8}	0.00014	3.264×10^{-6}
HP pressure	1.1584×10^{-7}	3.4997×10^{-10}	1.3502×10^{-5}	2.7478×10^{-6}
HP temperature	0.0001	0.0006	0.0258	6.4394×10^{-5}
HP flow rate	0.0765	190.1617	13.793	0.5297
HP enthalpy	2.2562×10^{-6}	1.4752×10^{-5}	0.0003	7.6123×10^{-8}
IP pressure	1.1584×10^{-7}	3.4997×10^{-10}	1.3502×10^{-5}	2.7478×10^{-6}
LP pressure	5.673×10^{-6}	1.0437×10^{-6}	0.0010	9.46689×10^{-5}
Exhaust pressure	1.6522×10^{-9}	7.129×10^{-13}	2.3234×10^{-6}	9.36019×10^{-5}
Exhaust temperature	5.3081×10^{-6}	6.7922×10^{-6}	0.0045	2.8694×10^{-5}
Exhaust enthalpy	4.981×10^{-5}	7.6735×10^{-5}	0.0084	0.0002
Turbine speed	0.0408	54.1245	7.3480	0.0006
Turbine power	0.0001	0.0007	0.0294	0.0008

5.3. Testing Scenario 3: Switch from Synchronized to Islanding Mode

Three main models are compared for the demand forecasting algorithm selection statistical models AR (auto regressive) and ARIMA (auto regressive integrated moving average) and RNN by LSTM. Results of this comparison are represented in Figure 22 and introduce prediction results for the selected period.

These predictions are fed to the operation optimization model of DT instances in order to manage sudden switches from the synchronized mode to islanding mode due to perturbations in the national grid. Switches are detected based on results communicated by DT instances analysis for anomalies detection. Valves opening are estimated according to developed regression models for control and taking into consideration generator health state, steam thermodynamic conditions, and power demand forecasting.

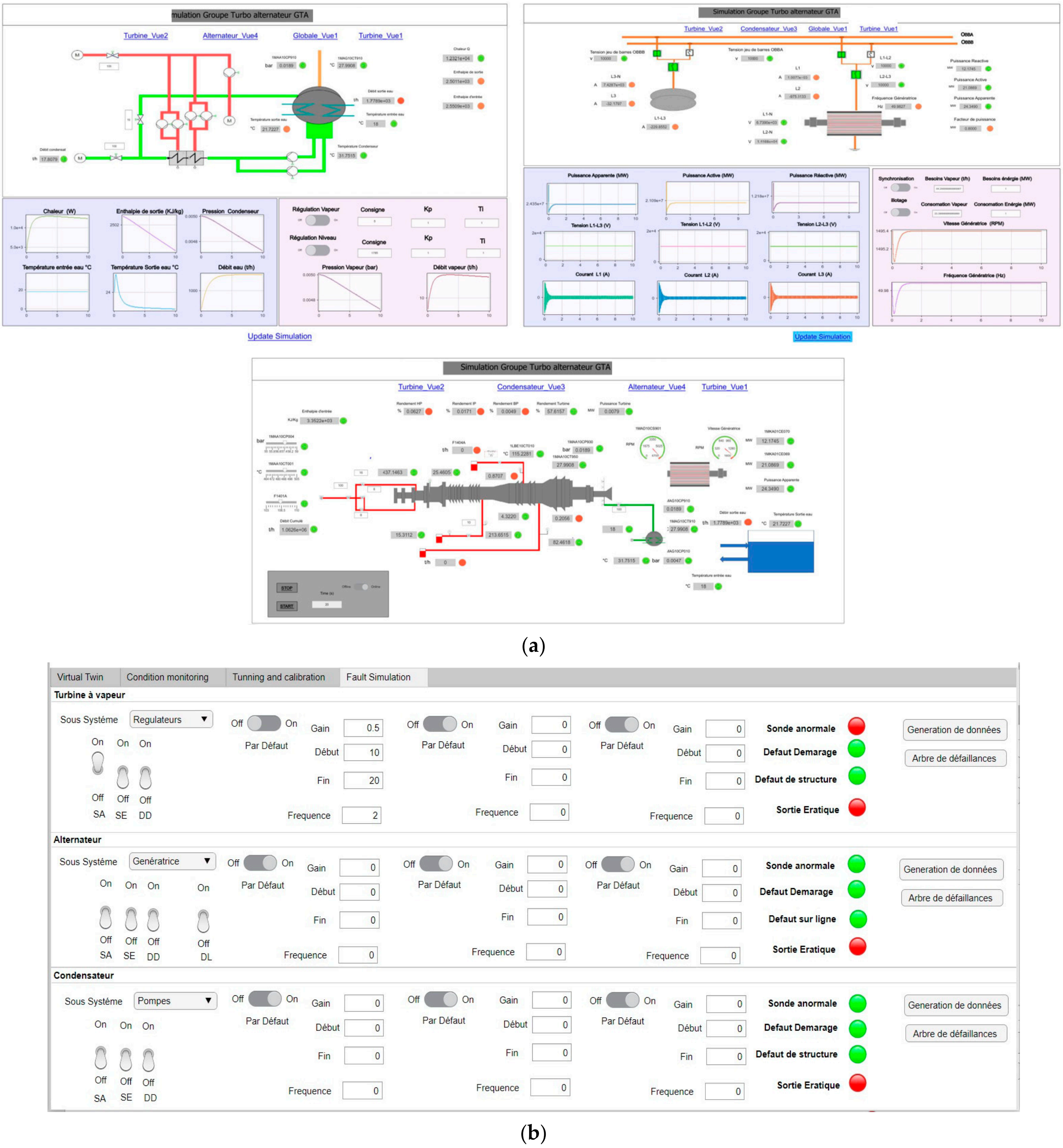
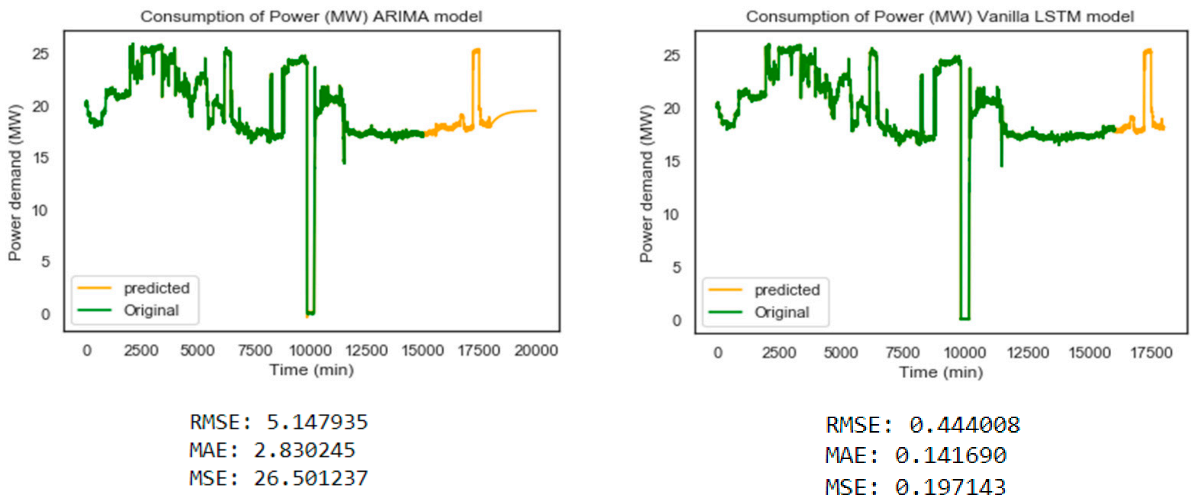


Figure 21. Virtual twin GUI for steam turbine, condenser and electrical generator condition monitoring (**a**). Fault simulation interface for synthetic data generation (**b**).



(**a**) (**b**)

Figure 22. Power demand forecasting performances based on ARIMA model (**a**). Power Demand forecasting performances based on LSTM Vanilla (**b**).

6. Discussion

6.1. Contributions to DT and TPP Concerns

We define two levels of assessment for the architecture. The first one concerns the functional evaluation of the modules constituting the architecture with regards to defined business concerns. The second level is specific to the internal structure of the developed twins with comparison to proposed state of the art solutions. Table 9 introduces state-of-the-art solutions proposed for TPP smart condition monitoring through grey box digital twin systems and hybrid agent-based models for collaborative prognostics combining DT black and grey box models with multiagent systems. The developed environment in MATLAB/Simulink based on a physics-based approach with a tuning mechanism that serves as a testing and simulation platform for DT types helps to overcome dynamic environment modeling limitations and robustness requirements for the underlying behaviors of real systems. The virtual environments share a common data broker with agent pools that enables it to communicate environment states and rewards as well as agents' actions to the environment. Testing and simulation of scenarios for DT type agents learning, and in-depth analysis is performed offline through the virtual environment. Models update according to systems performance evaluation and the degradation caused by the real environments enables DT types to keep track of real system state evolution. Model learning across both instances and types helps to reinforce models' accuracy on representing real assets behavior.

Table 9. Hybrid twins for power plants monitoring and DT-OMASE for smart prognostics.

	Ref.	Proposed Architecture			Models and Tools	Provided Services
		Domain	Links	Concerns		
Grey Box	[72]	Functional view Information view Usage view Communication view	DT-PT DT-User PT-DT DT-DT DT- Third party	Interoperability Security Awareness Communication Ergonomics Robustness	Net logo multi-agent systems K means clustering for agents' collaboration Empirical physical model of degradation	Anomaly detection Collaborative maintenance -Usage and maintenance phase
	[73]	Functional view Information view Usage view System view	DT-PT DT-User PT-DT DT-DT DT- Third party	Interoperability Security Awareness Ergonomics Robustness	Logical, kinematic and geometric models TCP/IP real time data communication Processing cycle and data integration	Assembly and virtual design and engineering of generators and turbines rotors -Manufacturing phase (rotor)

Table 9. *Cont.*

	Ref.	Proposed Architecture			Models and Tools	Provided Services
		Domain	Links	Concerns		
	[68]	Functional view Information view Communication view	DT-PT DT-User PT-DT DT-DT	Security Awareness Connectivity Ergonomics Robustness	Neural network Physics and electrical diagram system and controller	Supporting the physical twin throughout its life cycle -All life cycle phases included
	[71]	Functional view Information view Usage view System view Communication View	DT-PT DT-User PT-DT DT-DT DT-Third party	Interoperability Security Awareness Ergonomics Robustness	ANN Mechanical models based on the first principle of mechanics and differential equation	System dynamics and integration of operational data for the approximation of complex parameters -Design and engineering phase
	[7]	Functional view Information view Communication view	DT-PT DT-User PT-DT DT-Third party	Interoperability Security Awareness Connectivity Robustness	Thermodynamic model Approximation and linear regression	Representation of steam turbine control system modeling -Operation and maintenance
Hybrid agent based	[51]	Functional view Information view Usage view System view Communication View	DT-PT DT-User PT-DT DT-DT	Awareness Connectivity Interoperability Security and operational safety Robustness	Cosimulation alternatives through OPCUA and OSGi for selecting synchronization technology MATLAB is used for simulations of models; MAS module is developed with JAVA	Modeling and simulation of plant assets smart services for operation optimization -Operation and maintenance phase
	[33]	Functional view Information view Usage view System view	DT-PT DT-User PT-DT DT-DT	Awareness Connectivity Interoperability Security and operational safety Robustness	JACAMO framework is proposed for MAS development and REST API based on a service-oriented architecture SOA (Service-Oriented Architecture) for DT	Smart quality control and operation optimization -Operation and maintenance phase
	Ours	Functional view Information view Usage view Communication view Environment View System view	DT-PT DT-User PT-DT DT-Third Party DT-DT	Interoperability Security Awareness Connectivity Ergonomics Robustness Resiliency Traceability	OMASE for Architecture modeling MAT-LAB/SIMULINK for virtual environment modeling Python for agents' services development A MAS establishment	Power plant simulation and assets mirroring Collaborative prognostics and smart condition monitoring -All life cycle phases included

Table 9. *Cont.*

Ref.	Proposed Architecture			Models and Tools	Provided Services
	Domain	Links	Concerns		
[72]	Functional view Information view System view Communication View Security view	DT-PT DT-User PT-DT DT-DT DT-Third party software	Awareness Connectivity Interoperability Security and operational safety Robustness Traceability	Simulations are performed with Siemens Tacnomatix Process Simulated and OPC protocol for communication online and offline learning modules are developed on the top of the real system supervisory control system	Smart control and collaborative maintenance of plants assets Integration of DT into control architecture -Operation and maintenance
[73]	Functional view Information view Usage view System view	DT-User PT-DT DT-DT DT-Third party software	Awareness Communication Interoperability Ergonomics Robustness	Simulation of DT and agent's operation testing is performed on MATLAB through its set of Toolbox and Simulink for DES (discrete event simulation)	Mining trucks and shovels maintenance operations monitoring -Operation and maintenance phase

The establishment of a goal–role–capability model for each of the developed agent networks facilitate the implementation of a runtime verification module for agent's reorganization. This point is also integrated at the level of types and instances individual networks through DT manager agents that is responsible of evaluating agents' performances against a set of defined metrics that are included in a MAS platform and communicated to HMI agents by DT manager. Types and instances are connected by a coordination agent that ensures synchronization between the two networks. Unexpected events can be handled independently by the coordinator and communicated continuously to types that learn based on instances feedback and optimize communicated learning and forecasting parameters.

Separation of concerns and definition of views according to a viewpoint perspective applied by OMASE approach for agent modeling is proven to enhance developed DT architectures compliance to integration and maintainability requirements. The developed models by OMASE based on structure, definition of goals, and the integration of dynamic aspects into their definition can help developed twins align.

6.2. Limitations and Challenges of the Proposed Architecture

Potential limitations for the proposed DT-OMASE architecture revolves around three main concerns. The first concern is related to agents' communication scheme implementation.

Agents Networks communication: Current proposed version of the architecture is based on FIPA ACL communication scheme, which is based as we were able to see a set of developed communication acts and specifications proposed by a MAS community. Handling of increasing interactions of agents during runtime may require multiple reorganization cycles and thus lengthen the execution cycle time of some agents creating bottlenecks at key nodes of DT's network.

Confidentiality Constraints for industrial deployment: Our proposed policy for the development of a collaborative maintenance policy is based on the interaction between multiple instances, which requires continuous connections among agents within the network and development of significant case bases for each instance within the network. The robustness of this process can be put to the test by costs and confidentiality constraints with extended networks of assets and stakeholders communicating with the system.

Auction and bidding process challenges: Auction bidding protocol for similar cases selection and recommendation evaluation is fully dependent on establishment of connection between agents of the networks, processing time of bidding process and integration of real environment constraints, were not considered in the following use case. Testing of different scenarios can raise up several issues to be taking into consideration as to priorate clusters of assets targeted by the considered instance. Clustering of degradation profiles within networks of similar assets can be taken into consideration in order to restrict the scope of initiated auction and optimize auction processing metrics basically processing time and communication delays costs. Features considered within this use cases are all numerical features, which may affect selection process accuracy for different industrial applications with the integration of categorical features

7. Conclusions

Digital twins in the last few years have proven their great potential for intelligent decision making and life cycle management of complex systems. Leveraging this potential to its full extent is still limited by both functional and, more particularly, non-functional constraints that are related to the absence of a comprehensive framework for DT architectures development and the increasing complexity for representing real complex systems, emergent dynamics, and underlying interactions. Agent-based modeling enables the development of an interconnected, flexible, and interoperable architecture of intelligent and autonomous digital twin agents interacting in a structured framework allowing efficient information and knowledge transfer throughout complex industrial systems value chains. Recently, works on digital twins as we have seen through the analysis of the different hybrid twin architectures proposed have tried to harness the potential offered by analytic and physics-based models to improve developed digital twin solutions autonomy and intelligence. Nevertheless, most of them in their development phases focused only on purely technical aspects and therefore a systematic engineering approach was not considered. Our proposed method for developing an HT-OMASE architecture is based on the combination of viewpoint engineering for digital twins' views definition and requirements identification with multiagent development approach OMASE. OMASE offers an agile and flexible framework for the development of smart agents' organization which helps with the integration of the collaborative aspects triggered by both intelligence and autonomy and to unveil the underlying structure and interconnections developed through system operations within the physical environment. Environment dynamics modeling by a hybrid approach in addition to agents' dynamics representation by OMASE can both help to reinforce DT abilities for mimicking real system behaviors and initiate further development of DT business views. Through the proposed proof of the concept, we tried to shed light on the advantages of this fusion under a structured MAS defined framework. In the discussed use case, the use of reliability standards to define basic properties of the failure submodel will help fluent communication between the twin and third-party maintenance management software's inside the site for further prescriptive maintenance between the site's TPP. It also helps to develop DT agents' cognitive maps for enhanced autonomy. Future works will be focused on the implementation of the defined architecture modules and agents for DT maturity evaluation through domain standards and referential on the field and the development of agents' policy models for ethical considerations and the reorganization of agents against execution of path conflicts.

Author Contributions: Conceptualization, M.G. and B.S.; state of the art, M.G.; methodology, M.G.; simulation, M.G. and M.A.; validation, M.G. and M.A.; formal analysis, M.G.; investigation, M.G.; data curation, M.G.; writing—original draft preparation, M.G.; writing—review and editing, M.G. and B.S.; project administration, M.H.; funding acquisition, M.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Research Foundation for Development and Innovation in Science and Engineering and Innovation Lab for Operations (ILO).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: Work carried out within the framework of the cooperation agreement for technological and scientific development concluded between the UM6P and the FRDISI. We thank our colleagues from ILO and OCP group for their support and assistance.

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

Acronyms

Steam Turbine	
$\dot{m}$ *in*	flow rate at inlet (kg/s)
$\dot{m}$ *out*	flow rate at outlet (kg/s) *hin*: enthalpy at inlet (kJ/kg) *hout*: enthalpy at outlet (kJ/kg)
Q	heat rate (J)
W	work of non-conservative forces (J)
yi	condition at outlet (KPa)
xi	condition at inlet (KPa)
$\beta 0$	y-intercept constant
ϵ	residuals term
βp	slope coefficients for inlet conditions
T_{in}	section inlet Temperature (°C)
T_{out}	section outlet temperature (°C)
K	isentropic coefficient
$\dot{m}_{in}$	mass flow rate at inlet (kg/s)
$\dot{m}_{out}$	mass flow at outlet (kg/s)
V	section volume (m^3)
$\frac{\partial \varphi}{\partial P}$	density change due to pressure changes at constant temperature (s^2/m^2)
$P_{nominale}$	nominal pressure of sections (KPa)
$\dot{m}_{nominale}$	nominal flow rate of sections (kg/s)
$V_{Etageadmission}$	admission stage volume (m^3)
$r_{Etageadmission}$	wheel radius inlet stage (m)
$h_{Etageadmission}$	length inlet stage (m)
$\dot{m}_{roue}$	wheel flow rate (kg/s)
$\dot{m}_{admission-regule}$	regulated inlet flow through the 3 control valves (kg/s)
$H_{Etageadmission}$	length admission stage (m)
V_{IP-BP}	cross sections volume IP-BP (m^3)
r_{IP-BP}	cross section radius IP-BP (m)
H_{IP-BP}	cross section length IP-BP (m)
π_{adm}	ratio of nominal and actual admission pressure
π_{roue}	ratio of nominal and actual wheel pressure
$\pi_{soutirage1}$	ratio of nominal and actual extraction pressure
F_{HP}	power coefficient HP section
F_{IP}	power coefficient IP section
F_{LP}	power coefficient BP section
P_{HP}	power HP section (KJ/s)
P_{IP}	power IP section (KJ/s)
P_{BP}	power BP section (KJ/s)
$P_{Turbine}$	steam turbine total produced mechanical power
P_{Losses}	team turbine power losses
$\dot{m}_{Hp}$	HP section flow rate (kg/s)
η_{is-HP}	isentropic coefficient
h_{roue}	wheel enthalpy (kJ/kg)
$h_{extraction,s}$	extraction enthalpy (kJ/kg)
$\dot{m}_{Ip}$	HP section flow rate (kg/s)

η_{is-IP}	isentropic coefficient IP
$h_{soutirage1,s}$	IP extraction enthalpy (kJ/kg)
$\dot{m}_{soutirage1}$	flow rate LP extraction (kg/s)
$\dot{m}_{\mathrm{soutirage2}}$	flow rate IP extraction (kg/s)
$\dot{m}_{CO}$	cross section flow rate (kg/s)
η_{is-LP}	isentropic coefficient LP
h_{CO}	enthalpy IP-LP (kJ/kg)
$\mathrm{h}_{echapement,s}$	exhaust enthalpy (kJ/kg)
$\mathrm{h}_{\mathrm{soutirage2,s}}$	extraction 2 enthalpy (kJ/kg)
Generator	
J_{Δ}	moment of inertia (kg.m^2)
T_m	mechanical torque (N.m)
T_e	electrical torque (N.m)
ω_m	rotor speed (rpm)
D_{ω}	damping factor
Q	reactive power (MVA)
P	active power (MW)
U	current voltage (V)
I	current intensity (A)
θ	rotation angle (rad)
δ	Delta power angle (rad)
x	generator reactance
ξ	damping ratio
L	cyclic inductance (H)
Steam Condenser	
$\dot{m}^{Exhaust_{steam}}$	flow rate exhaust steam (kg/s)
$\dot{m}^{Condensate}$	flow rate condenser (kg/s)
T^{in_water}	inlet temperature cooling water (°C)
T^{out_water}	outlet temperature cooling water (°C)
$\dot{m}^{water}$	flow rate cooling water (kg/s)
M^{water}	cooling water mass (kg)
Q	heat exchange ratio (KW)
C_p	thermal capacity of the cooling water (KJ/KgK)
$T^{condensate}$	condenser temperature (°C)
$V^{Condenser}$	condenser volume (m^3)
R	condenser specific constant KJ/(KgK)

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