Intelligent Hybrid Heat Management System: Overcoming Challenges and Improving Efficiency

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The research delves into intelligent hybrid heat management Systems, exploring the challenges faced and solutions for enhancing efficiency. Hybrid heating systems are complex cyber-technical systems that combine city heating networks with renewable energy sources, such as heat pumps and solar panels. Traditional heating systems often lack adaptability to internal and external conditions, leading to suboptimal performance and user expectations. This paper proposes a new approach by integrating smart technologies, the Internet of Things, Artificial Intelligence, Machine Learning, optimization techniques, and trade-offs into the management of hybrid heat systems. The emphasis is also placed on the fact that the introduction of smart technologies makes it possible to make hybrid heating systems human-oriented and meet individual needs. Energy efficiency improvement is achievable by combining solutions, such as actual forecasting, with intelligent management that adapts to changing climates and user behaviors. The challenges addressed include inadequate responsiveness to load changes, inaccurate heat consumption forecasting, and inefficient data management. The paper emphasizes the need for intelligent systems that comply with the current standards, providing cost optimization, socializing and ensuring resilience, customer orientation, reliability, safety, and trustworthiness. This exploration of intelligent hybrid heat management systems seeks to overcome existing challenges and pave the way for a sustainable, digitally optimized future in district heating systems.

Keywords — intelligent management, cyber-technical system, data efficiency, forecasting, Internet of Things, trustworthiness.

I. Introduction

Today, many technical systems used to ensure human life, comfort, and health can be considered socio-technical. In this context, district heating systems have gone through a long evolutionary path and have reached the point where they should be considered as a hierarchical unification of technical systems, and thus their transformation into so-called “cyber-technical systems” with society and its individual representatives. A person in such a combined system is a consumer of services produced by the technical system.

Using heat from fossil fuels for heating purposes is one of the oldest energy uses. Unfortunately, fossil fuels are a finite resource. In addition, fuel combustion increases CO_2 and greenhouse gas emissions, harming the environment. Therefore, the evolution of heat supply systems is aimed at the joint use of various types of fuel combustion and renewable energy sources, transforming traditional heating systems into hybrid ones. At the same time, they strive to increase energy efficiency at all stages of the energy life cycle: in generating thermal energy, its transmission, storage, and utilization. However, economic, environmental, and social factors influence the evolution of heating networks. The economic factors include the cost of energy resources and the cost of operating the heating network.

Environmental factors include the desire to reduce the amount of fuel burned and, consequently, lower CO_2 and greenhouse gas emissions [1]. This becomes the driving force for introducing additional non-carbon energy sources, such as heat pumps, solar panels, etc., into existing heating networks and developing technologies to conserve heat energy, minimize losses, and facilitate the effective joint utilization of various heat sources.

Economic and environmental factors are closely intertwined, mutually influencing each other, since the cost and availability of energy resources usually correlate with the environmental friendliness of their usage. Therefore, economic criteria are vital for optimizing processes when designing and operating heating systems. Social factors, such as accessibility, individual needs, and gender differences in heat energy use, are not considered. The amount of heat supplied is regulated by the norms and rules for the provision of services.

Economic transformations, climate change, and technological development enable a shift in the perception and evaluation of traditional and hybrid technical systems, making the human consumer of services the determining factor in creating and operating heating systems. This shift introduces a significant contradiction. While heating systems are designed to satisfy people, the particular needs of both society and individuals may remain unsatisfied.

Developing Internet of Things technologies, cloud technologies, Machine Learning, and Artificial Intelligence can change the approach to cyber-technical systems and make them more human-centered.

This research will be aimed to:

- Evaluate the possibility of energy efficiency improvement achievable by combining forecasting with intelligent management that adapts to changing climates and user behaviors.
- Evaluate the new approach integrating intelligent technologies, the Internet of Things, Artificial Intelligence, Machine Learning, optimization techniques, and trade-offs in managing hybrid heat systems.
- Propose an intelligent agent interaction system scheme with a dynamic interaction definition based on formalized knowledge and semantic models.

II. Literature Review

The impact of crises like the COVID-19 pandemic, climate change, digital transformation, and the development of Artificial Intelligence methods is reshaping the ways and methods of energy utilization. The Digital Energy Futures from Monash University [2] shows that the needs of energy system users are projected to change significantly by 2030-2050. The demand for individual comfort, especially in a comfortable microclimate, is expected to rise, given that people will spend most of their time indoors. Accordingly, services providing a comfortable microclimate are expected to operate reliably and meet the growing need for comfort.

The trend towards increasing heat energy consumption has been noticeable for a considerable period. The study by Sustainability Victoria [3] shows that a significant portion of the energy is dedicated to providing heat. The heating and cooling of buildings and industry constitute half of the energy consumption in the European Union. Despite various energy-saving measures, 75% of heat energy is still produced from fossil fuels [4]. Furthermore, the research works in [5, 6] emphasize that the need for heat among household consumers continues to increase yearly.

Volt et al. [7] underscores the significant potential of district heating systems for modernization and transformation, noting that these systems are not equally represented in all EU member states and cover approximately 12% of European heating and cooling demand. District heating networks are prevalent in Eastern and Northern European countries. The centralization of heat production enables the control and reduction of CO_2 emissions. Additionally, it is also highlighted in [8, 9] that introducing renewable energy sources into district heating systems positively enhances energy efficiency.

The increase in components and heat sources is transforming the control mechanism of heating systems. Using Big Data, the Internet of Things, and Artificial Intelligence technologies, digitalization facilitates cost-effective optimization for network operators while empowering end users [7]. Smart heat meters, thermostats, sensors, and controllers allow enhanced monitoring and control. In addition, Artificial Intelligence methods make it possible to develop real-time optimization methods for heating networks. On the other hand, introducing modern intelligent technologies poses new challenges, such as the complexity of managing big data [10], ensuring data reliability and security, maintaining confidentiality, sustaining intelligent solutions, and fostering trust in them. Intellectualizing heating systems can improve their economic, environmental, and social efficiency. Modern intelligent technologies will become the solution that enables the socialization of cyber-technical systems, making them more human-centered and more consistent with end users' expectations [11].

III. Problem Statsment

The energy efficiency of hybrid heat systems can be increased through measures aimed at reducing heat losses or by improving the efficiency of heat energy utilization. The first way to improve energy efficiency is aimed at optimizing heat transfer without additional losses, so it primarily concerns the modernization of buildings and heating system elements. Examples of measures to minimize heat losses include insulating walls, replacing windows, upgrading pipelines, optimizing pumps for warm water circulation, etc.

The second method to improve energy efficiency relies on the rational management of the heat network, considering variations in climatic characteristics inside and outside buildings and user behavior. The effectiveness of this method is measured by its ability to meet user needs and ensure thermal comfort.

Currently, heating network management systems lack sufficient intelligence. The design and operation of heating systems are carried out only by considering cost optimization, reducing heat loss, and reducing the amount of heat supplied just to reduce the cost of this service. These systems now define user needs in terms of providing heat in accordance with existing sanitary standards. Also, the economic factor – especially the cost of heat energy–plays a determining role, with all other factors either ignored or considered secondary. These management systems lack proactivity, and changes occur only in response to events that have already happened. The transition from one mode to another is carried out by an automated control system based on the feedback principle as a response to the discrepancy established due to temperature measurement at the current moment with the possible required mode. It is also challenging to determine what the required mode may be in the near future. Heat systems exhibit significant inertia, and the transition from one temperature mode to another occurs over long periods of time [12]. This characteristic can be used as an advantage, enabling heat retention in buildings for a long time without the need for additional generation. The inertia of heating systems and the time distribution of the transition process from one state to another make forecasting difficult.

The following problems are significant and require immediate solutions:

- Inadequate response to load changes: Automated control systems may have limited ability to adapt to internal or external changes, such as changes in temperature, weather conditions, or operating modes. To control the heating system of a building or group of buildings, PI or, in some cases, PID controllers are used. They work in limited ranges and monitor only 2-3 key indicators. Their task is to smooth out peaks and bring the heating system parameters according to a predetermined temperature curve. In addition, the temperature curve itself may not correspond to the real state and require adjustments that the automated system, due to its design features, cannot make.
- Lack of accurate forecasting: Forecasting heat consumption can be problematic, especially during unforeseen changes. The actuality of forecasting in this context is considered more broadly. Actual forecasting means not only that it is close to the actual value but that it corresponds to the moment in time, the technical capabilities of the heating system, and the needs of the consumer.
- Inefficient data management: Processing and analyzing large volumes of data can be challenging for management systems.

Taken together, all these factors create customer dissatisfaction.

The introduction of trustworthy Artificial Intelligence [13] and digital technologies is intended to ensure not only the cost optimization of district heating systems but also to make them more resilient, sustainable, customer-oriented, reliable, safe, and trustworthy. This research aims to analyze existing problems with data, forecasting, and the socialization of hybrid heat systems and explore ways and means of overcoming them.

In a particular context, it is necessary to investigate problems with data, forecasting, and the socialization of modern hybrid heat systems.

The central hypothesis of this study. Resilience, sustainability, customer centricity, reliability, safety, and trustworthiness in managing hybrid heat systems can be achieved by moving from the classic automatic control and monitoring oriented perspective typically in district heating management to a more customer-oriented perspective based on Artificial Intelligent solutions and Cloud-IoT architecture.

IV. The Three E Principle

The functioning process of heating systems can be divided into three subprocesses that ensure the required energy efficiency and are supported by various technical solutions implemented in various monitoring, control, and energy consumption accounting systems. Conventionally, they can be referred to as the “three E” principle: energy consumption, energy use, and energy management.

During the energy consumption process, the current energy consumption of the facility and the potential for utilizing available energy sources are assessed. The energy use process analyzes energy conversion efficiency in different facility elements. The facility’s necessary operating modes are determined in the energy management process.

Individual components of the "three E" principle interact with each other. The degree of their relationship is assessed in the form of a Venn diagram, as shown in Fig. 1, where the intersection of two sets shows common properties or performed tasks, and the area of the intersection of three sets represents the achievement of the required energy efficiency of the object. For example, by jointly considering the components of "energy consumption " (EC) and "energy use" (EU)–M_1, it is possible to solve the task of accounting for consumed energy resources and analyze the structure of the distribution of energy resources consumption. The joint performance of the components of "energy management" (EM) and "energy consumption"–M_2 allows one to assess the influence of regulation and optimization methods on the overall consumption of resources. Considering the combined "energy management" and "energy use"–M_3 establishes the influence of regulation and optimization methods on individual indicators of the quality of transformation and distribution of energy resources, considering economic factors.

Fig. 1 shows the Venn diagram and the processes subordinate to it (Table 1), correspond to discrete logical models according to set theory:

$$\begin{cases} M_1 = EC \cap EU = (a \cup b \cup c \cup d) \cap (e \cup f); \\ M_2 = EC \cap EM = (a \cup b \cup c \cup d) \cap (r \cup o); \\ M_3 = EU \cap EM = (e \cup f) \cap (r \cup o); \\ EF = M_1 \cap M_2 \cap M_3, \end{cases} \tag{1}$$

where M_1, M_2, and M_3 are the result of joint consideration and implementation of the components of the "three E" principle, where EC, EU, and EM correspond to energy consumption, energy use, and energy management, respectively; a, b, c, d, e, f, r, o are sets of processes characterizing individual components of EC, EU, EM according to the Table I.

Energy efficiency (EF) can be achieved due to the synergy of each component of the “three E” principle. This confirms the need to create an intelligent decision-making system to combine all processes of the “three E” principle.

A system of commercial accounting of consumed heat, a system for monitoring the performance of the heating system, and an automated heat consumption control system have the features of cyber-technical systems implemented using

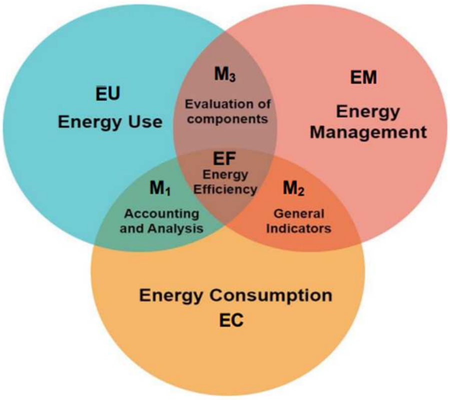

Fig. 1. Venn diagram of the «three E» principle

Internet of Things technology. These systems use data collected from smart meters and sensors, allowing us to hope that synergy can be achieved through the implementation of intelligent solutions. It should also be taken into account that intelligent solutions can bridge the gap between users and cyber-technical systems (Fig. 2).

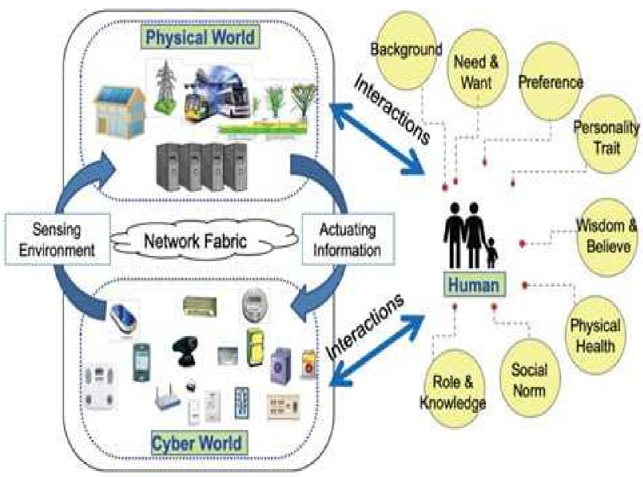

Fig. 2. A cyber-technical system focused on provisioning individual human needs

The next section of this paper analyzes the components that make IoT systems proactive, intelligent, and human-centric for hybrid heat systems.

V. Results

In addition to combining the Internet of Things, information, and communication technologies with traditional district heating technology and additional heat sources, intelligent hybrid heating also incorporates solutions based on Machine Learning, multi-objective optimization, and search for rational and/or compromise solutions.

The task of heat supply systems is to maintain microclimate conditions in buildings at a level that provides comfort to the consumer of this service.

The temperature in the premises at any given moment depends on many external factors, such as the temperature of the outside air, weather (wind, sunlight), the energy efficiency of the materials from which the building is constructed, the design features of the heating network inside the building, etc.

TABLE I. Generalized characteristics of the components of the "three E" principle and their processes and variables

Components	Systems	Processes	Multiple variables, characteristics, or methods
ENERGY CONSUMPTION (EC) - assessment of the facility's current energy consumption and the potential of using available energy sources	System of commercial accounting of consumed heat	Classification of objects, **a**	Object types and indicators
		Assessment of possible energy, **b**	Types and assessment of the power of energy sources
		Assessment of required energy for facilities, **c**	Estimated indicators of energy consumption
		Control and accounting of energy consumption, **d**	Measured energy consumption indicators
ENERGY USE (EU) - analysis of the efficiency of energy conversion and establishing the distribution of its losses by types and on various elements of the object	System for monitoring the performance of the heating system	Assessment of energy conversion processes, **e**	Indicators and characteristics of conversion quality (energy monitoring)
		Assessment of energy distribution processes, **f**	Indicators and distribution of energy losses (energy budget)
ENERGY MANAGEMENT – formation of the necessary operating modes of the object, which ensures regulation of technological parameters and optimization of energy consumption	Automated heat consumption control system	Regulation of the operation of objects, **r**	Methods and means of regulation
		Optimization of energy consumption, **o**	Criteria, methods, and means of optimizing energy consumption taking into account economic indicators

An example of the dependence of the temperature in the premises on the heat of the heating system and the external temperature is in [14].

Heat consumption in a building is controlled by reducing the flow of heat water or lowering its temperature at the entrance to the heating system of the building. This is a time-dependent process. Accordingly, if the management of the heating system uses the time factor appropriately, it can significantly reduce the cost of heat consumption without reducing the comfort for consumers. Wernstedt et al. [15] show in what time intervals the air in the building can cool down with a different flow of warm water into the heating system.

Under real-world conditions, heating systems must reliably and continuously supply heat to customers, heat service is offered at certain time intervals.

During operation, metering devices - heat meters and sensors - determine the current state of the heating system.

The wide distribution of communication capabilities of the global Internet allows modern devices for metering consumed resources, which have a high accuracy class and implement the function of measuring, calculating, storing, and transmitting data. At the same time, the transfer of data from sensors and meters is automated and allows you to create systems for monitoring the current parameters of heating systems in real-time and to accumulate and save data over a long period.

Perekrest et al. [16] show that a traditional district heating system at a basic level is represented as a set of interacting or separate feedback systems of the control loop. In this case, this management cycle has three main parts: measurement, analysis, and action. To make such a system "intelligent," it is necessary to consider all parts of this cycle. At every stage of the management cycle, there are unresolved problems.

Hybrid heating management systems can become "intelligent" by overcoming problems of inadequate response to load changes, more accurate forecasting, and more efficient data management. Thus, control systems must monitor the current state of the heating system and determine which modes it can enter in the next time interval in response to changes in external factors and simultaneously provide the required efficiency, environmental friendliness, and comfort.

Next, the features of forecasting, data management, and improving how you respond to change to ensure customer satisfaction will be considered.

A. Forecasting

Forecasting makes the processes of "Three E" more proactive. In the energy consumption process, forecasting is used to find methods and ways to prioritize adaptive activities for efficient use of resources. The efficiency resource can be found as a result of analyzing user behavior over time [17] and consumption profile [18]. Historical data arrays and long-term and short-term forecasting methods can be used in this context.

To analyze heat energy consumption, autoregressive models [19–21], time series analysis methods [22], k-NN classifications, and forecasting methods based on artificial neural networks [23–25] are used. The accuracy and efficiency of forecasting is highly dependent on the data used

In the energy use process, forecasting is used as analytics to determine possible failures and methods for their prevention. This approach allows for creating a maintenance program and schedules to extend the assets' life and optimize their productivity. Digital experts connected through application software interfaces (APIs) can be involved in formulating the final decision.

The most common energy management method is control based on a temperature curve in a weather-compensated or time-dependent controller. The analysis process in the control cycle of hybrid thermal systems is most often ensured by forecasting the possible need of a building for thermal energy at the current moment under the existing influences of external factors. Using such analytics in the control process allows the control system to be more flexible and respond to changes in the internal and external parameters of the heating system.

In this case, the temperature curve must reflect the actual demand for heat load when the external factors affecting the heating system change. The use of Machine Learning methods allows the use of historical data that characterizes the heat load demand of a building instead of a complex mathematical apparatus to describe the heat balance of a building. For example, the Random Forest (RF) method [26] and support vector machines (SVM) [27] can be used to predict the temperature curve of the coolant temperature in a heating system controlled by data from an electronic weather-dependent controller. The Random Forest machine learning method can run on the user's computing devices, which allows this method to be successfully used to adjust the mode of the heating system in response to changes in external factors [28].

Proactive management of heat supply can be implemented as the selection of the most achievable, from the point of view of practical implementation, at a given current moment in time, heat system mode. Effective forecasting can determine the amount of heat required at a given current moment in time. In this case, forecast models can be built based on a nonlinear autoregressive neural network with exogenous inputs, which combines aggregate data regarding climatic conditions, operating schedules, heat consumption of the building, and data from previous forecasts [29].

Parfenenko et al. [30] show that the choice of the feasibility of the operating mode and its compliance with the needs of consumers can be made based on fuzzy rules formulated by experts.

The accuracy and efficiency of forecasting depend on the data, the chosen forecasting methods, and the computing capabilities of the user's devices.

Forecasting models can be organized into services that relate to forecasting or data processing. The in-depth analysis that forecasting services are capable of doing will improve the heating systems' economic, environmental, and social efficiency and make the management process more proactive.

B. Data Analysis and Data Mining

The problem of processing and storing data is primarily related to data confidentiality. Data must be delimited. User data characterizing user behavior and data on heat use over previous long periods must be stored on the user's side. This allows for minimizing the risks of data interception and unauthorized use. This local data storage ensures fast and reliable access to it with minimal latency. Along with its advantages, storing data locally has a significant disadvantage. This requires creating a particular infrastructure for storing and processing data, which can be difficult and expensive. In addition, with the complete concentration of data only on the user's side, it is difficult to carry out the energy use and energy consumption procedures of the "three E" principle.

Customer data processing can be enabled by edge computing. In this case, edge computing should consist of advanced data processing services (such as Artificial Intelligence and Machine Learning) deployed directly on the facility at the data source, while computing nodes can be connected to the cloud for automatic functionality or security updates, remote access, etc. One of the advantages of local data processing is low processing latency and fast recall time compared to cloud services. This allows advanced data processing services to process data without a guaranteed Internet connection. This way, even critical services can operate reliably and uninterruptedly. In addition, the software components of the data processing system can be instantly updated, and new functionality can be added throughout the entire life cycle.

Connecting computing nodes to the cloud allows you to differentiate user access, organize a secure connection, perform operational monitoring of all nodes and components, maintain their computing relevance, reduce the number of system failures, determine the priority of calculations and data processing, increase the productivity of the cyber-technical system, as well as optimize work processes and energy efficiency.

Figure 3 shows a data flow diagram of a proactive management system for a hybrid heating system. The management system must be flexible enough and be able to characterizing the achievability of the assigned tasks and customer satisfaction. In addition, predicting the many possible states of a heating system requires storing a set of historical data and using forecasting models on this data. Considering the above, we argue that an intelligent management system should have sets of components for saving various types of data, in both the short and the long term; models for transforming and evaluating data; forecasting models; components for processing expert opinions and extracting knowledge from them; and models for choosing a compromise. These models and components can be launched and supported by intelligent agents.

The data distribution, storage, and management of models remain unsolved.

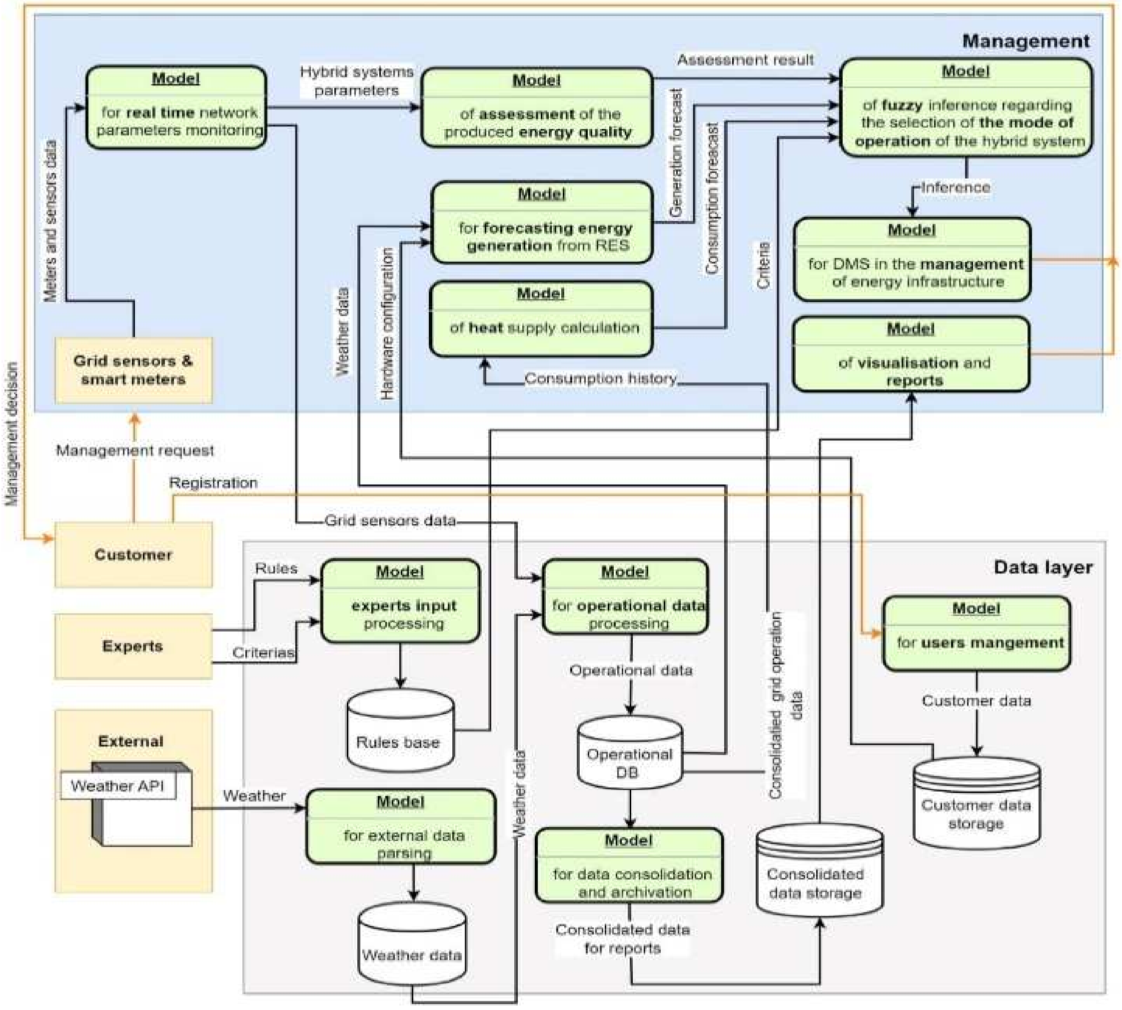

Fig. 3. A data flow diagram of a proactive management system for a hybrid heating system

adaptively reconfigure the operating modes of the hybrid heating system depending on the emerging requirements for it and the influence of external factors. The proactivity of the management system lies in the fact that at the current moment in time, it must select such a mode of operation for the heating system, which is both technically achievable in the time allocated for it and be a compromise in terms of economic efficiency, environmental friendliness, and consumer satisfaction. Flexibility and adaptability are ensured by real-time data collection and processing. Data collection should include not only quantitative indicators of the current state of the hybrid heating system and its components and the external environment but also qualitative and quantitative indicators

C. Intelligent Solusions

According to the “three E” principle, energy efficiency is achieved due to economic and environmental optimization of heat provision while constantly maintaining the quality of service for each client. Thus, energy efficiency strives to achieve several goals simultaneously, and reducing the cost of heat energy consumption and increasing the level of consumer comfort may be in conflict. Achieving energy efficiency requires finding a combination of adequate behavior policies for the heating system and load control strategies. On the other hand, these strategies must meet the requirements of operational optimization and correspond to the technical capabilities of the heating system at a fixed point in time. In this regard, the problem of achieving energy efficiency cannot be considered a multi-object optimization problem. However, it should be assumed that there are problems in choosing an achievable and compromised mode of operation for the heating system at each fixed point in time, in which most factors are uncertain. Also uncertain is the model that allows it to adequately describe and consider all existing changing conditions when searching for a solution.

The development of Artificial Intelligence methods makes it possible to determine optimization goals and scenarios for choosing modes without formally setting goals for the heating system's functioning, making it possible to quickly make practical decisions regarding changing the scenario for executing the assigned task. In addition, Artificial Intelligence methods ensure the sustainability and proactiveness of decisions in cases that require adjustment to new operating goals. The need for such adjustment may arise in the following circumstances:

- The emergence of new helpful information about the state of the object, situations that can be used to achieve greater energy efficiency;
- Unexpected failure of elements and components of the heating system and the need to switch to additional or more environmentally friendly sources of thermal energy;
- Changes in decision-making criteria, etc.

To realize the synergy of the “three E” principle, it is necessary to build a system of interaction between intelligent agents whose activities are based on the methodology of the general theory of intelligent information technologies and systems, ontological analysis, data mining, Machine Learning, knowledge models and simulation modeling.

Such a system (Fig. 4), based on formalized knowledge and semantic models, will optimize the process of interaction of various heat sources and, at the same time, divide the tasks of each category of the “three E” principle into subtasks. Intelligent agents can use this formal knowledge to make decisions during the execution of tasks. The ontological model should describe the characteristics of various operating modes and scenarios depending on changing conditions and requirements for the heating system. In this intelligent management system, the definition of interaction scenarios between the heating system’s models and modes will be abstract and will be supplemented with details automatically through a dynamic expert system (knowledge base); thus, the interaction system functions as a service system based on ontologies that include a rational choice of the architecture for the interaction of intelligent agents and the models they serve.

Further research directions could focus on determining the criteria for choosing an optimal or compromising solution; creating models to assess the performance indicators of the selected solution; creating ontological models; and exploring methods for creating a knowledge base, a dynamic expert system, and intelligent agents.

VI. Conclusion

Heat energy consumption is growing, but most come from fossil fuels, highlighting the need for renewable sources. The "three E" principle - energy use, energy consumption, and energy management - represents an approach to energy efficiency in hybrid heating systems, working together to achieve optimal results. The introduction of intelligent technologies makes it possible to bridge the gap between users and cyber-technical systems, making them more human-oriented and meeting individual needs.

Intelligent hybrid heating combines traditional district heating technologies with the Internet of Things and intelligent solutions based on Machine Learning and optimization. Forecasting in the energy consumption process allows activities to be tailored to efficiently use resources based on analyzing the consumption profile and user behavior over time. Based on semantic models, the intelligent agent interaction system enables allows to optimize the interaction process and apply formal knowledge to decision-making under various conditions.

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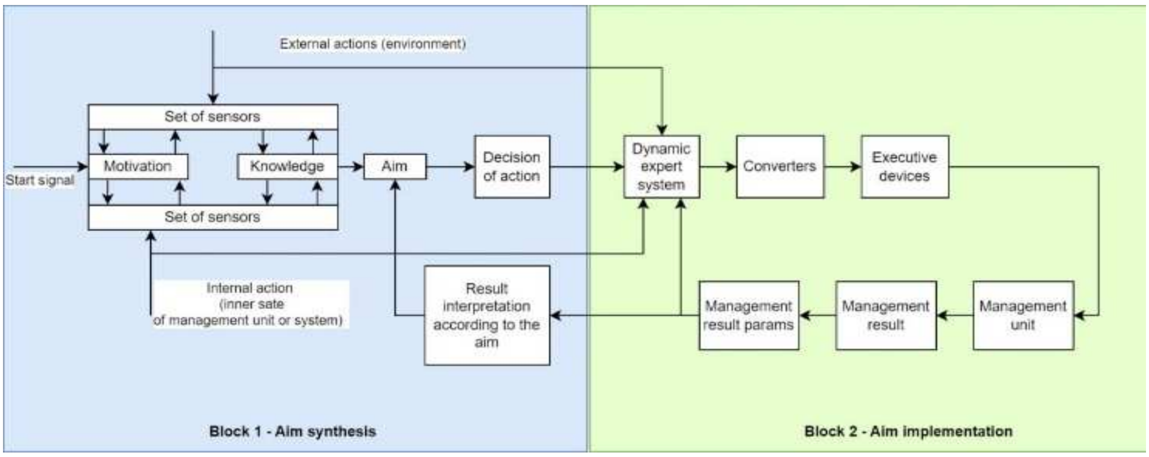

Fig. 4. Block diagram of an intelligent agent interaction system with dynamic interaction definition

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