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The Effect of Distributed Load Balanced System Architecture in the Production Cost of Heat Energy Generated in the District Heating System with Change in End User Consumption.

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ABSTRACT

The purpose of this research is to dynamically control the district heating system using demand-side-management strategies. Demand-side-management are claimed to have a number of positive effects, e.g., lower production costs, reduced usage of fossil fuel (kerosene and gas), and improved production capacity to serve an increased number of consumers. This work will implements an intelligent demand-side management strategies in district heating systems using Q-learning. The fundamental idea behind this approach is that proper understanding on how a large number of local decisions with apparently minimal impact, can have large impact on the overall system performance. It is imperative to design a combination of mobile agents that can optimize these varying local decisions with maximizing the quality of service delivered. In order to evaluate the approach, a fine-grained simulation tool that simulates a complete district heating system was built. This work included the development of novel simulation models, often by integrating existing ones. The simulation tool simulates a district heating system to functionally and dynamically support interaction at each time step with the multi-agent system. The tool enables detailed performance analysis of both district heating systems as well as of different strategies of the control system. Results from simulation studies indicate that the approach makes it possible to reduce production cost while maintaining the quality of service.

Keynote: District heating system, Intelligent system, Q-learning, Mobile agent, Load balance , multi Agent

INTRODUCTION

This paper is basically on the distributed load balanced system architecture in the production cost of heat energy generated in the district heating of a system

A scenario approach to handle with high complexity and the adequacies of centralized approaches is to specialize and decentralize action. The general idea is to divide subsystem, i.e., to partition the complex problem into a number of simpler sub-problems that can be solved in a distribution control in DHS manner, and whose individual solution contribute to the solution of the actual complex problem. Basically, a number of interacting decisions making takes the place of a single centralized decision maker of option. Note many manufacturers have introduced advanced application of Intelligent Electronic Devices (IED) into their products that can perform functions such as parameter configuration and monitoring and control. The possibility to connect these distributed IED in a Local Area Network (LAN) promise highly dynamic systems. However, the problem of providing a suitable framework for managing the connected devices remains. Also the IED are reactive and is not enabled to learn the long term characteristics of the system. There is a continuous search for concepts and abstractions to facilitate the design and implementation of systems based on Q-learning. One such concept is software agents (Wooldridge, 2018).

They are modelled as reactive systems; hence they do not have the ability to learn the long term characteristics of the environment. The most common model for distributed automation and control systems is probably the Supervisory Control and data Acquisition (SCADA) model. The SCADA model is centralized by nature. From a central reading location, a master station monitors a number of remote sites (substations) equipped with remote telemetry units. The remote units measure various conditions and report the data back to the master station, which is carrying out the necessary analysis and control functions.

2. OVERVIEW

2.1: Combined District Heating for Network Allocation

A sustainable and environmental friendly energy supply flexible and efficient distribution control systems. The factors are used to implement systems intelligent coordination of (smart grid approaches) and which evolves the integration of different energy sectors. "Managing the interdependencies in different activities" (Wernstedt *et a*l., 2019). From the MAS perspective coordination is a process in which agents engage in order to ensure that a community of individual agents acts in a coherent manner (Bellifemine *et a*l., 2017). The paper introduces the unified energy agent as an agent-based approach for a comprehensive modeling and control of energy conversion systems. This technique enables synchronize simulation and optimization of coupled energy networks, and then in a next step, the development of corresponding smart grid solutions to be applied in the field. It is applicable for the simulation of integrated of various networks which are presented by a real world use case of an innovative combined heat and electrical network conquer, which was implemented for the city of Lemgo, Germany. Preliminary results from the project are discussed and an outlook on future work is given for researchers.

2:2 District Heating System through Recycle Optimum.

Operational optimization of district heating systems with temperature limited sources (Samvan and Ivopoth, 2020) Future district heating systems (DHS) will be supplied by renewable sources, most of which are limited in temperature and flow rate. Therefore, operational optimization of DHS is needed to maximize the use of renewable sources and minimize (fossil) peak loads. In his paper, they present a robust and fast model predictive control approach to use the thermal mass of buildings as a daily storage without violating temperature constraints which coordination was not considered. The objective of this paper incorporates two elements. First, they focus on an operational control strategy that explicitly accounts for temperature limited renewable sources, like a geothermal source. Secondly, the optimization problem is modelled based on convex optimization problem, which is required for adoption of model predictive control in rational formulation. The result show that the peak heating demand can be reduced by 50%, if the thermal inertia of the buildings is used and the heating set points are adapted.

2:3 District Heating circuit to the Downstream of the LP Economizer

This controls the stored temperature that been need at a particular domain than otherwise seen in a power generation cycle, but is ultimately constrained by, stored dispersion, white plume, or exhaust dew point considerations based on weather. (Aringhieri and Malucelli, 2019), and the possibility to use heat as by product from industrial processes, District heating in this work is special variety of cogeneration wherein process steam is supplied at very low pressure and typically high flows to heat water for distribution operation. The Maximum extraction of supply will be constrained by the needs to retain high steam flow to the LP turbine. In a situation where some customer may need steam extraction from the steam turbine network, requiring the LP steam turbine to be declutched entirely. Since the temperature at this point required for district heating is low (typically less than 111°C) it is also advantageous to plus a district heating circuit to the downstream of the LP economizer. This allows additional exhaust gas energy to be recovered beyond that necessary to economize, evaporate, and superheat the steam for the steam turbine. However, due to the large distances the distribution of heat is also the largest managerial planning problem, the distribution time can get quite large, typically range in 24 hours. Factors that have an effect on the heat load can be classified into three groups listed below:

- Weather conditions: Approximately 70 percent of the total heat load can be attributed to outdoor (ambient) temperature (Lehtoranta et al 2016), other weather conditions affecting the heat load are for example, humidity, solar radiation, wind direction and velocity.
- Human factors: The consumption of domestic hot water is mainly dependent on social behavior.
- Physical factors of the distribution network: Factors such as length, isolation and dimension of distribution pipes determines the amount of distribution losses. Approximately 10 percent of the total heat load is attributed to distribution losses (Fredriksen and Werner, 2009).

Today, the operation of most DHS is based on a simple mapping between the ambient temperature and the temperature of the water in the supply network.

2:4 District Heating Systems Control cooling

It is obvious that an optimization model of a large district heating system with many loops and more than one heat production plant is extremely computationally demanding (Milgate, 2017). District heating and cooling technologies with and without seasonal storage the first of these is a step-by-step approach. The growth of a district heating network in this case can best be accommodated by starting with small heating only plants or by retrofitting turbines of existing peaking or intermediate load power plants, located close to the heat load centers. As the system grows, large base load district heating power plants can be introduced, with a high capacity factor already assured. Heating chambers of the plant will thereafter serve as peaking and standby units. Combinatorial optimization problem are hard because there is no assign formula for solving them exactly. Every approach has to be examined in order to find the best alternate solution and the number of possibilities increases exponentially as the size of the problem increases. Furthermore, it is argued that when the complexity of a district heating system reaches its peak equal to 100 components and restrictions of distribution, the present equipped computer software become insufficient to find an optimum operational strategy (Fox et al., 2016).

3. METHODOLOGY

3:1 The Model for the Distributed Heating System Domain

In this section, the model for the distribution district heating system application is used in this thesis to solve the problem space under investigation with illustration. Attention will be restricted to the distribution part of the supply network, see Figure 3.1.

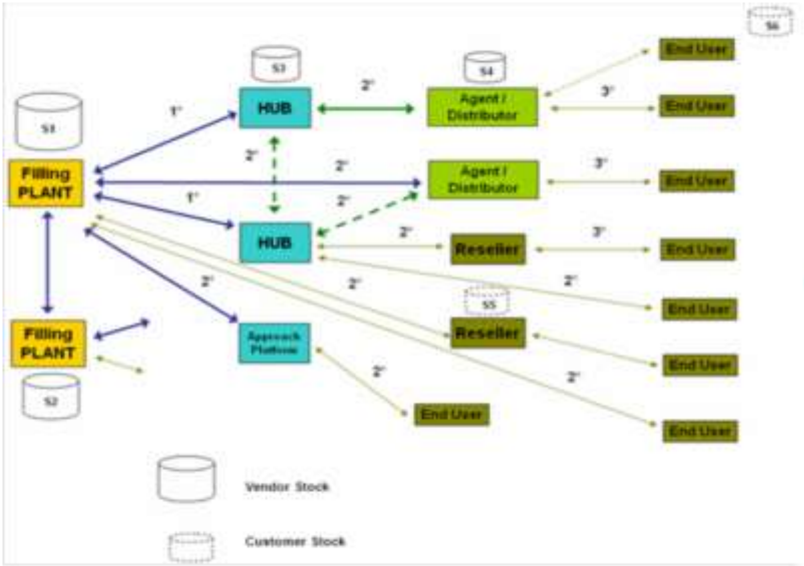

Figure 3.1: An Example of a Small Production and Distribution Network where there are two Producers (s1-2), two Distribution centers (s3-4), and seven Customers (s5-7)

The facility location decisions are suboptimal, production, inventory and distribution plans are fully optimized, and the supply chain may still be operating efficiently. Therefore, for determining the best network configuration, all the costs at the levels need to be taken into account to optimize the system wide production, control, inventory and distribution costs.

Thus, the system is model complete on supply chain vendor stock networks, e.g., the details of the production process within the producer and interaction with sub-contractors is modeled. However, believe that the simplifications made do not change the applicability of the general approach which suggested. The approach is to divide the description of the production and distribution network in three different parts, production, distribution and consumption under the costumer stock.

3:2 Multiple Processes Agent coordination Action for an Environment

The train agents using parallel computing code rule which studied and an environment for policy and acted open for value function of the state. The parallel pool client S^1_{ki+1} (the process starts the training) sends precision of the agent and environment to each parallel worker. Each worker runs through the agent of Hub world within the environment and sends data back to the client for verification S^2_{k2}. The client agent learns from the data environment sent by the workers and sends the updated policy parameters back to the workers field. This configures the training r^2_{k2} the environment coding done by the workers and the learning is done by the client within the domain of the environment. Specifically, the workers update the agent S^1_{k1} against the environment, and send experimental data (reward observation, action, and next observation, and a termination signal state) to the client for policy. The client then computes the gradients from exponent updates the network parameters S^n_{kn+1} and sends the updated parameters back to the workers via HMI, which continue to update the agent with the new parameters which communicate to customer within the substation for end user as seen in figure 3.6 bellow.

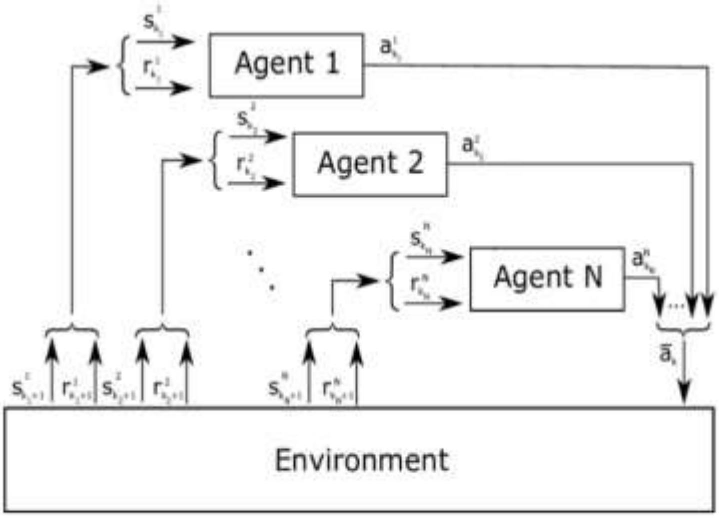

Figure 3.2 Multiple Processes Multi Agent System Action Coordination

3:3 Equivalence of Forward and Backward Views policy

This section show that off-line TD (λ), as defined by various parameters show, achieves the same weight updates as the off-line λ return controller to ascertain it goal. In this section the forward and backward views of TD (λ). Let $\Delta V_t^{\lambda}(s_t)$ denote the update at time t of $V(s_t)$ according to the (λ) return and let $\Delta V_t^{TD}(s)$ denote the update at time t of state S according to the mechanistic definition of TD (λ) as given then the goal is to show that the sum of all the updates over an episode is the same for the controllers for effective results for improved policy:

$\sum_{t=0}^{T-1} \Delta Vt^{TD}s = \sum_{t=0}^{T-1} \Delta Vt^{\lambda}(st)$, I_{sst}, for all s Ɛ s 3.1

$\sum_{t=0}^{T-1} \Delta Vt^{TD}s = \sum_{t=0}^{T-1} \Delta Vt^{\lambda}(st)$, 3.2

$\sum_{t=0}^{T-1} \Delta Vt^{TD}s = \sum_{t=0}^{T-1} ά ð(ϒ⁄\!\!\lambda)^{t-k} Iss$, 3.3

$\sum_{t=0}^{T-1} \Delta Vt^{TD}s = \sum_{t=0}^{T-1} ά ð(ϒ⁄\!\!\lambda)^{t-k} IQk$, 3.4

$\sum_{t=0}^{T-1} \Delta Vt^{TD}s = \sum_{t=0}^{T-1} ά(ϒ⁄\!\!\lambda)^{t-k} IQL$, 3.5

$\sum_{t=0}^{T-1} \Delta Vt^{TD}s = \sum_{t=0}^{T-1} ά \quad (ϒ⁄\!\!\lambda)^{t-k} dk$, 3.6

$\sum_{t=0}^{T-1} \Delta Vt^{TD}s = \sum_{t=0}^{T-1} ά\bar{I}ss(ϒ⁄\!\!\lambda)^{t-k} ḓk$, 3.7

Where I_{sst} is an identity indicator function, equal to 1 if $s = s_t$ and equal to 0 otherwise?

First order that an accumulating eligibility trace can be written in explicitly (non recursively) as

$e(s) \sum_{t=0}^{T-1} QVt^{\lambda}(st\, s, a)$, 3.8

Production:

Let $P = (p_1 \ldots\ldots p_n)$ be the set of all producers and $K = (k_1 \ldots\ldots k_m)$ be the set of all commodities. $L = (l_1 \ldots l_n)$ set of filling station. Then for each pair of producer, p Є P, and commodity, k Є K, denote;

The production time, α_{pk}
The production cost, β_{pk}
The production capacity, λ_{pk}
The production at time t, δ_{pkt}

Distribution:

Let the distribution network be a directed graph D = (N, E), where N = P Ừ C Ừ I is the set of all nodes, $I = (i_1 \ldots\ldots i_t)$ is the set of all internal distribution nodes, C is the set of all customers, and D agent distributor.

$E = (e_1 \ldots\ldots e_q)$ is the set of all edges. Here an edge corresponds to a distribution channel between two nodes (there may be more than one edge between two nodes) and, N, is indexed as

$(N_1,\ldots,N_n,N_{n+1},\ldots,N_{n+p},N_{n+p+1},..,N_{n+p+r})$ …….. 3.9

Then for each pair of edge, e Є E, and commodity, k Є K, then key note is denoted;

The distribution time, ε_{ek}
The distribution cost, ϕ_{ek}
The distribution capacity, $Ʇ_{ek}$
The distribution at time t, η_{ekt}

For each pair of node, n Є N, and commodity, k Є K, then key note is denoted:

The buffer cost, μ_{nk}
The buffer capacity, $ɷ_{nkt}$
The deterioration rate, θ_k
For each commodity, k Є K, then key note is denoted:

Consumption:

Let $C = (c_1 \ldots\ldots c_p)$ be the set of all customers. Then for
Each pair of customer, C Є C, and commodity, k Є K, denote;
The consumption at time t, $ϫ_{dkt}$
The demand at time t, σ_{ckt}

Although this model is used to analyze production and distribution costs etc. are linear, it can be used to describe many interesting production and distribution problems using this Q-Learning model. Furthermore, there might be constraints and dependencies between different commodities concerning production, distribution, and buffer capacities. Note that the production, distribution, and buffer dynamics are part of the solution rather than the problem, and that is possible amount of consumption which is governed by these dynamics for effectiveness control of required products.

3.4 Multi-agent System Architecture for Decentralized Control of DHS Based Q-learning

The aim of this objective is to improve the monitoring and control of district heating systems through the use of agent technology. In order to increase the knowledge about the different states the district heating system can be in, i.e. the different consumer levels for hot water by the various substations is stored by the Q-learning agent. This is as opposed to the knowledge of only the current and future state in a district heating as devised by the previous researcher. In the previous model, the heat supply by the distributed heating system was dependent on the demand from the various substations. This led to fluctuations in supply by the DHS. The advantage here is that Q-learning can be used to store the various states of the district heating systems. This has the advantage of knowing different states, i.e. consumption levels of the various substations, thereby assigning Q-values parameters to them. This will help the intelligent agent to better predict the optimum consumption level of the substation at all times. Additionally since the Q-learning continuously update the data from current interaction with the system, the time for the redistribution agents to converge to the consumption needs of the substations will be minimized.

In the Q-learning system at the producer side, each substation is equipped with an agent that stores all consumption levels of all substations. This makes the prediction of the consumption at any instant in time easy because of the higher number of state spaces present in the model as opposed to limited state space present in the previous researcher's model. The contributions to the consumers will be higher quality of service, e.g., better ways to deal with major shortages of heat water, which is facilitated by the interaction of the agent with the system in learning how to cope with these cases through the introduction of redistribution agents, and lower costs since less energy is needed for the heat production.

When it comes to a multi-agent system (MAS) in a district heating system, the role is that each agent implements autonomous actions in order to optimally run the substations models in a dynamic system order concurrently. Based on the study, the hierarchical central local agent structure is embedded in the district heating system controller models to balance the energy consumption and the consumer's comfort. A multi-object particle swarm optimization (PSO) technique is utilized for optimizing intelligent management, for instance, in a district heating system, the central agent communicates with the substations (consumers) agent to decide the optimal power distribution to each substation by considering their comfort demand. A substation agent, on the other hand, communicates with consumers and decides energy demand. The local agents take care of temperature control, water flow in pipes, expansions in pipes due to heat and air quality control. The objective function aims at maximizing total thermal comfort and minimizing energy consumption to customer. Similar central local systems utilize Q-Learning controllers for maximizing the thermal comfort. Through Q flow standard initiated for learning of table as seen in figure 3.7 Standard Q-learning update for the parameters decision taking action

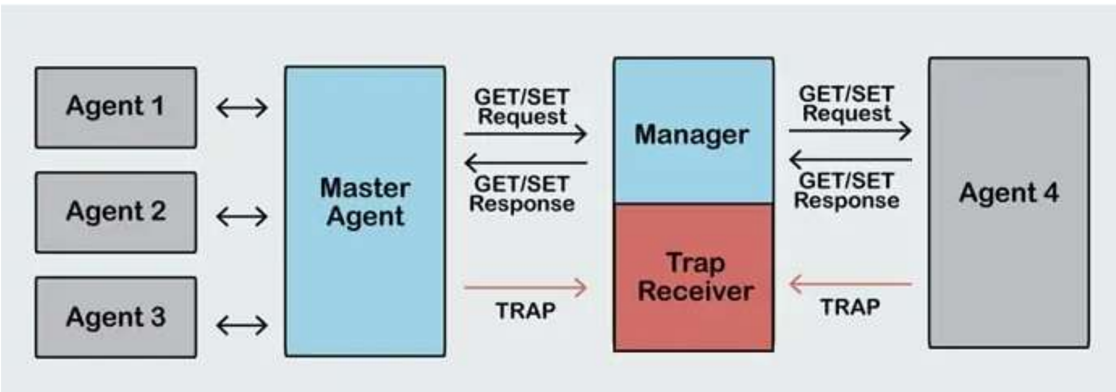

Figure 3.3 Standard agent updates policy for the parameters decision taking

SNMP messages are categorized into five basic types such as TRAP, GET, GET-NEXT, GET-RESPONSE, and SET which incorporate with q-learning agent. It is entity that is responsible for communication agent with SNMP for query the agent for further use, obtain get the responds from the agent, set variable in the agent and acknowledge the synchronous event to display on HMI for field work on data presentation.

3:5 The MAS Distribution Heating System Simulator (Operational) Model

The simulation model for the real time control of the district heating system for optimization of Q-learning and its different modules are described. First the description of the requirements will be outlined; this is followed by an analysis of these requirements. Then the design and implementation of the simulator are presented. Finally, the validation of the decision making control hierarchy for DHC systems operation is shown in figure 3.10. A typical Mile prediction horizon is 6–12h controller. The lower control layer corresponds to a fast time scale model that handles the basic regulation action of process variables of model domain, such as configuration of action, temperature supply, mass flow rate and pressure, at the substation building level is based on decision making which show control operation supply for customers.

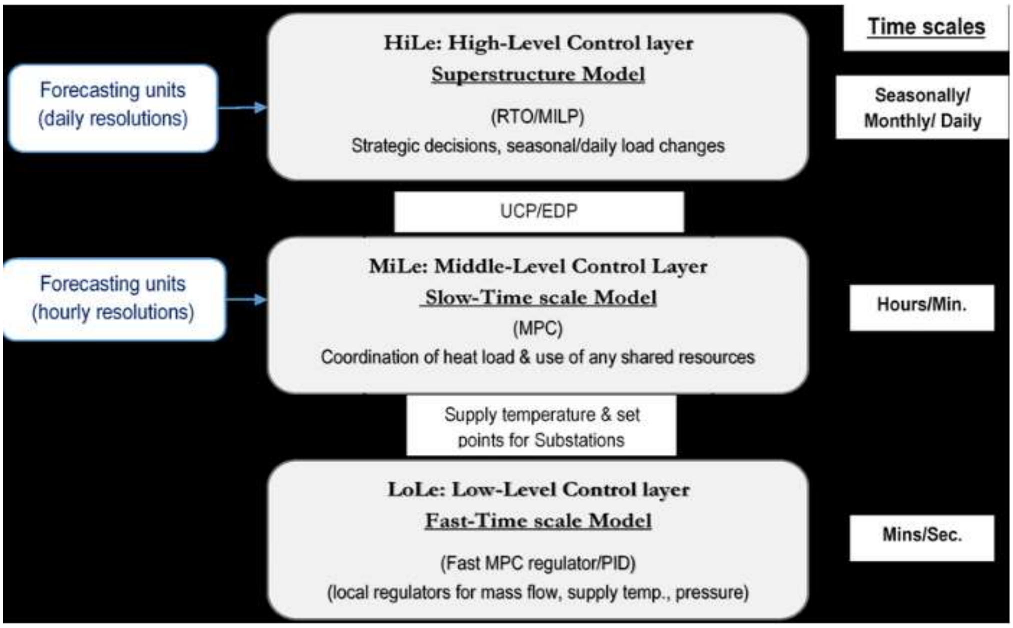

Figure 3.4 Decision making control hierarchy for DHC systems operation.

Supporting Q-Learning-Based Tools efficient forecast are necessary components for DHC planning in networks supply for customer playing a key role in operational decision making. Hot water forecasting for customers could be a crucial contributing factor for estimating future district heating demand in DHS. Several weather parameters, such as temperature, solar radiation, atmospheric pressure, humidity and precipitation, are widely available are been required

3.6 The DHS Simulation Setup

The following is a complete list of the measurement gauges as well as their position indicated by a graphical view of the experimental system. The experimental setup is shown in figure 3.36

Measurement Primary Side:

Name	**Type**	**Unit**	**Comment**
Office A	Temperature	ºC	Primary in
Office B	Temperature	ºC	Primary out
Office C	Temperature	ºC	Primary in
Office D	Temperature	ºC	Primary out
Office E	Diff. pressure	Bar	Primary dp 0-6 Bar
Office F	Diff. pressure	Bar	Primary dp 0-6 Bar
Office G	Volume flow	l/s	Primary flow
Office H	Volume flow	l/s	Primary flow

Measurement Substation A, Secondary Side:

Name	**Type**	**Unit**	**Comment**
Office A	Temperature	ºC	Cold water in
Office B	Temperature	ºC	Hot water out
Office C	Temperature	ºC	from radiator
Office D	Temperature	ºC	To radiator
Office E	Temperature	ºC	VVC return
Office F	Volume flow	l/s	Radiator flow
Office G	Volume flow	l/s	Domestic hot water
Office H	Volume flow	l/s	VVC flow

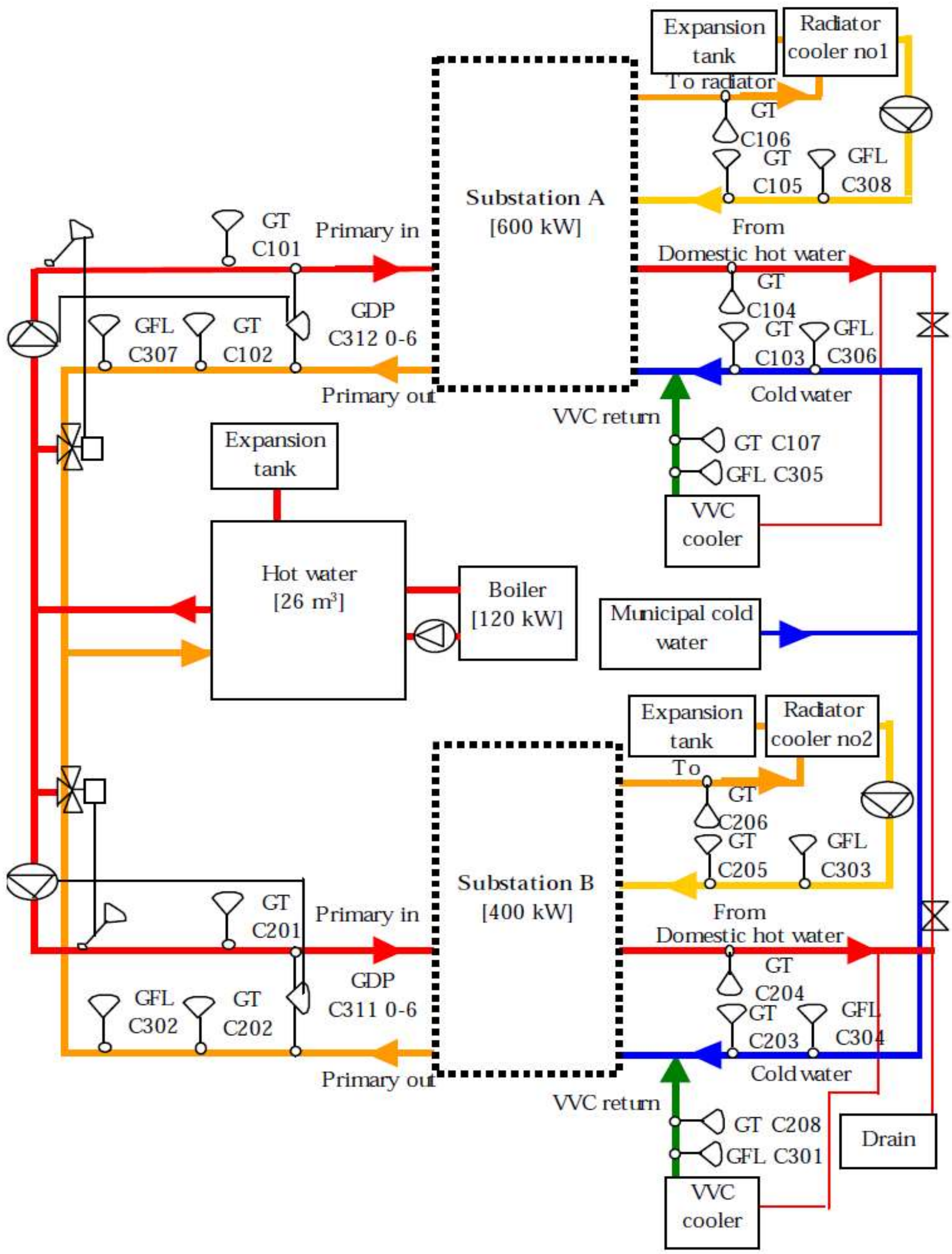

Figure 3.5 Experimental set-ups the heating supply system with the waste heat Recovery system using an Absorption heat pump

4. DATA PRESENTATION

4:1 Results and Discussions for Distributed Load Balancing

Table 4.1: Distribution operation control

Time (s)	**(KW)**
0	0
0.1000	-14.8965
0.2000	-43.1728
0.3000	-64.4573
0.4000	-71.8871
0.5000	-77.6626
0.6000	-78.5398
0.7000	-63.4604
0.8000	-36.0709
0.9000	-9.0312
1.0000	5.4925
1.1000	2.4564
1.2000	-14.2548
1.3000	-34.7543
1.4000	-48.6584
1.5000	-50.1342
1.6000	-40.1031
1.7000	-24.9071
1.8000	-12.5412
1.9000	-8.5867
2.0000	-13.8414
2.1000	-24.5644
2.2000	-34.8738
2.3000	-39.8607
2.4000	-37.8239
2.5000	-30.6677
2.6000	-22.5107
2.7000	-15.4837
2.8000	-10.2307
2.9000	-7.5190
3.0000	-7.3817
3.1000	-8.8302
3.2000	-10.3254
3.3000	-10.5396
3.4000	-8.9482
3.5000	-5.9693
3.6000	-2.6357
3.7000	-0.0157
3.8000	1.3061
3.9000	1.4469
4.0000	1.0772
4.1000	1.0250
4.2000	1.8565
4.3000	3.6381
4.4000	5.9699
4.5000	8.2398
4.6000	9.9460
4.7000	10.9240
4.8000	11.3816
4.9000	11.7497
5.0000	12.4459
5.1000	13.6746
5.2000	15.3571
5.3000	17.2066
5.4000	18.8936
5.5000	20.2100
5.6000	21.1537

5.7000	21.9023
5.8000	22.7038
5.9000	20.9359
6.0000	13.5919
6.1000	1.5099
6.2000	-11.0957
6.3000	-19.3193
6.4000	-20.3166
6.5000	-14.6400
6.6000	-5.6904
6.7000	2.1749
6.8000	5.7700

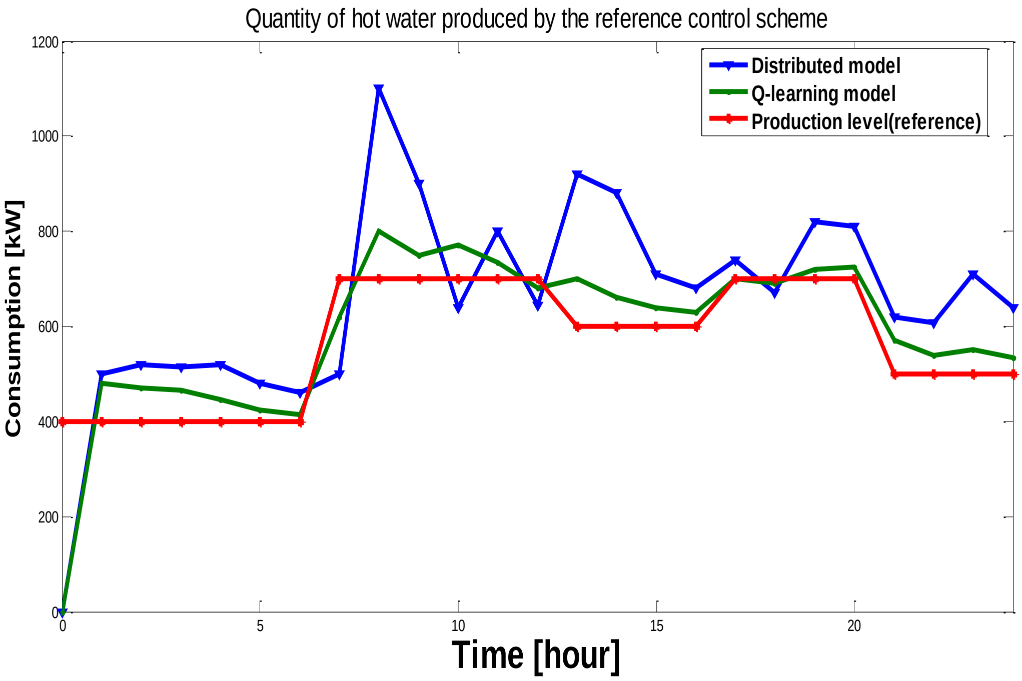

Figure 4.2 The amount of hot water produced by the reference control scheme indicated by the red line, indicating 0% surplus production), compared to the 5-day average consumption

For the work, two series of simulation experiments have been made. In each experiment there were one producer agent and one redistribution agent (since a cluster is independent of other clusters, only one cluster needs to be simulated. In each experiment the district heating system was simulated for 24 hours. Each experiment was run over 5 different days (different series of consumption values) and the averages are shown

4.2 Result and DISCUSSION of DHS heat load, as obtained for the case network supply.

Table 4.2 Sub process a network supply				
TEMPERATURE				
STREAM NAME	INLET T_{IN} [°C]	OUTLET T_{OUT} [°C]	CP [MW/°C]	HEAT LOAD ΔH [MWH]
HOTA1	240.0	130.0	40	49.00
COLDA1	185.0	220.0	50	17.50
	300	500	60	30.00
	500	550	70	50.00
	600	700	80	70.00
	700	800	90	80.00

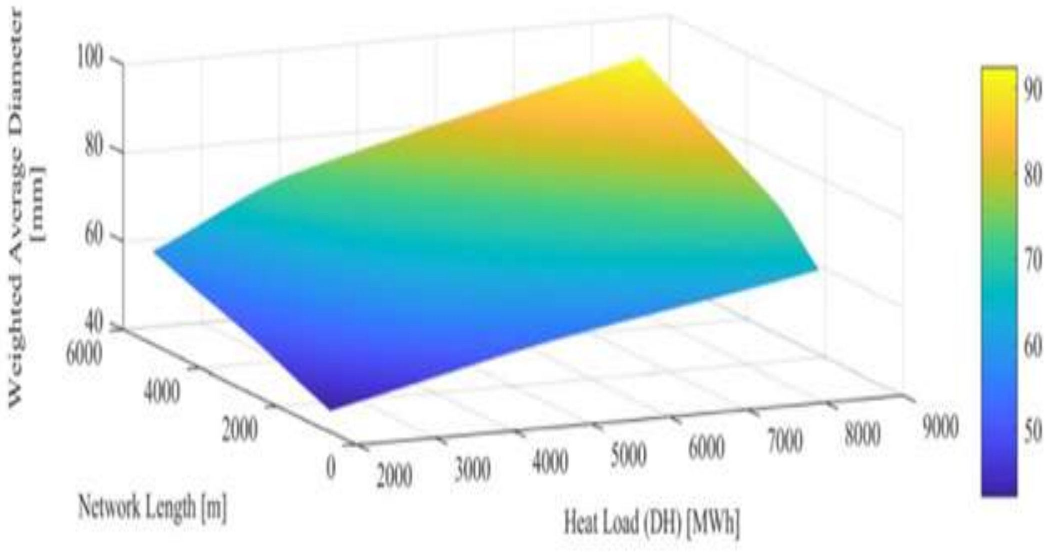

Figure 4.2 weighted average diameter as a function of the DHS overall network length and the DHS heat load, as obtained for the case network.

Figure 4.2 illustrates the DHS network in the point of linear heat density by the simultaneous changes at the DHS network length and the overall heat load, weighted average diameter there changing as to the linear heat density. That is obvious that with each change of the parameters in question (CN and L) there was a need to re-dimension the DHS network supply, The design condition was considered to be with parameters, the operational strategy being based on the weather-compensation curve (other strategies were formed to use the same pipe dimensions). The total supplies found for each of the nominal diameters are given promising for supply products to various substations for the customer.

CONCLUSION

In conclusion the operators and the consumers, will be provision of efficacy higher quality of service, e.g., better ways to deal with major shortages of heat water or excess heat water, and lower costs, i.e., less energy is needed to produce the heat water. Since the heating of water often is associated with burning fuel (kerosene and gas) that pollutes the air in one way or another, the project obviously contributes to increase the quality of life in our nation.

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