Optimal Scheduling for a District Cooling System with Chilled Water Storage: Comparative Assessment of Vapour Compression and Absorption Refrigeration Cycles

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District cooling (DC) systems are able to exploit locally available energy in order to supply cooling to local end-users through an integrated DC network. The present work aims at obtaining the critical decisions in the performance of a DC network at the operating level. End-users can be of different type (e.g., residential or commercial) with different demand profiles and an optimal strategy needs to be employed in order to satisfy the demand and minimise energy usage. In published literature the vast majority of the studies employ simplified mathematical models in order to describe the thermodynamic cycle used and only a handful of studies take into account the actual dynamics of the system transition from one state to the other as well as the time delay attributed to the cooling medium transfer through the network. The critical decisions involve the operating conditions and optimal allocation for the cooing of existing units in a suitable time interval, which form the basis for the satisfaction of requirements in cooling under demand variability. Although reduced order models of the process of ABR cycle are used, the time delay of the cooling medium transfer through the pipes is considered through the employment of validated first order plus time delay models. The proposed optimisation framework enables the identification of demand driven, highly performing solutions through the direct consideration of all interacting factors over a pre-defined time horizon. Optimal results include the definition of the optimal allocation of produced cooling effect in such way that cooling demand is always satisfied.

1. Introduction

The idea of DC is to exploit locally available energy resources in order to satisfy end-user cooling needs. A coolant is circulated through a DC network from a local cooling plant to the customers, which can be residential, commercial or industrial buildings. DC can offer increased energy efficiency and a number of economic and environmental benefits (Powel et al., 2014) compared to the use of individual cooling machines. The established equipment used in DC is the vapour compression cycle (VCR) which uses electricity as energy resource in order to produce the cooling effect. The absorption refrigeration cycle (ABR) is a promising alternative to VCR, that exploits heat as the energy resource to produce the cooling effect. Renewable heat, geothermal wells, solar collectors or biomass (or natural gas) are some of the available energy resources that can power ABR cycles. Usually, several units are employed in a single DC network, resulting in a problem of optimal selection and scheduling of the operation of each one in order to match the cooling demand and reduce operating cost. Until now a number of optimisation models have been presented, including linear, non-linear, mixed integer linear and mixed integer non-linear programming (MINLP) models, to define the optimal scheduling strategy of the DC system. Discrete variables usually refer to the number of equipment in the network, the start-up status, and so forth. The continuous variables refer to energy resource, stream split ratios, and so forth (Deng et al., 2017). The non-linear parts of the processes are associated with the thermodynamics and the heat transfer processes, which are usually represented using simplified models.

Deng et al. (2017) presented a MINLP model for the optimal scheduling of district heating and cooling, and illustrated a strategy of zero waste of cooling energy and cost saving of 24.3 % up to 63.9 %. The subsystem modelling was performed through simplified models that were not formally validated, while the optimal scheduling model was discretised in time using 1 h intervals. On another study, Lu et al. (2015) used MINLP to solve the optimal scheduling problem by minimising the overall operating cost. The models of the subsystems were simplified, discrete (steady-state) models that did not include the dynamics of the process. Li et al. (2019) proposed a hybrid optimisation-based scheduling strategy, based on a genetic algorithm and dynamic programming, for combined cooling, heating and power generation (CCHP) and were able to increase the performance by 1.92 %. Similarly, the models employed in this study were simplified and did not take into account the dynamics of each subsystem. On a different approach, Chen et al. (2020) presented the optimal scheduling of an integrated electricity and district heating system considering the dynamic characteristics of the heating network. The model included time delays and considered heat losses but the main focus of the investigation was the analysis of the impact time delays and heat losses had in the obtained results. Similarly, Nova-Rincon et al. (2020) performed dynamic optimisation including the mass flow profiles in the DC network to examine the possibility of the so called low ΔT syndrome. The proposed model used orthogonal collocation on finite elements and exhibited low computational effort to reach the optimal solution.

The above literature review shows that, with only a few exceptions in the most recently published literature, the problem of optimal scheduling in DC systems uses simplified mathematical models for the sub processes. More importantly, the models do not take into account the dynamic response of the cooling load variation through time. The approach employed in this work aims at obtaining critical decisions in the performance of a DC network, that comprises different types of end-users (e.g., residential and/or commercial) and of units of different distance from the end-user, at the operating level. The critical decisions involve the operating conditions and optimal allocation for the cooling load requirements to existing units within a suitable time interval under cooling load demand variability. At this level, short term variability of resource availability and demand fluctuation mainly determine the optimal conditions and the cooling distribution decisions. Although reduced order models of the process of ABR cycle are used, the transportation time delay of the cooling medium through the piping is considered and validated models of the first order plus time delay type are employed. The proposed optimisation framework enables the identification of demand driven, highly performing solutions through the direct consideration of all interacting factors over a pre-defined time horizon.

2. Models and Methods

The mathematical modelling of the ABR units is performed through regressed, first order dynamic models based on simulation results of a validated non-linear dynamic mathematical model previously developed in ASPEN Plus Dynamics (Aspen Plus, 2021), a process simulation software previously considered as ideas for the ABR system simulation (Gkouletsos et al., 2019). At first, a steady state mathematical model is developed in ASPEN Plus, which is then converted to its dynamic analogue in ASPEN Plus Dynamics. Consecutively, an appropriate control system is designed in order to be able to obtain closed loop simulation results. This step is necessary due to the fact that the closed loop dynamic response can be described by surrogate models and the performance of the system can be simulated without the need to actually include control algorithm equations that increase model complexity and subsequently solution computational effort. The dynamic surrogate model is generated on the basis of a regressed first order transfer function based on dynamic closed loop simulation results, while the required cooling capacity of the cycle is varied. The model has as input the generator external heat input and as output the evaporator cooling capacity. Additional models are developed to describe the time delay expected by the cooling medium transfer through the network pipelines. The single effect, non-linear dynamic model developed in this work is detailed in Kyriakides et al. (2020).

2.1 Control layout of the single effect ABR flowsheet

In order to be able to perform the dynamic simulation of the single effect ABR system a performance optimization multivariable control algorithm needs to be designed and implemented. As shown in Figure 1, the imposed control strategy can be divided in four categories, namely temperature control, level control, flowrate control and capacity control. The first three levels serve the monitoring and control purposes of key process variables indicative of the performance of the evaporator and generator, while the latter serves for the regulation of the system's capacity. In total seven single-input single-output (SISO) feedback PI controllers are utilised by the control strategy. A schematic of the flowsheet including the controllers is presented in Figure 1.

2.2 Reduced order models

In order to reduce the computational effort to realistic levels for practical implementation required for the DC network behaviour prediction via simulation, reduced-order models are selected to represent each process.

Model parameters are estimated via regression on simulated dynamic transients. The cooling generation quantities are related to the required energy resource for the capacity range and the operating modes of interest. The process model incorporates two sub-processes. The first is associated to the ABR unit used to produce the cooling effect. The second is connected to the transport of the cooling medium to the site of demand.
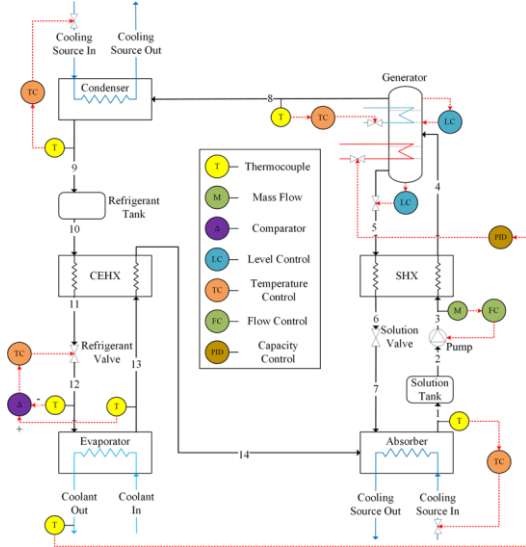

Figure 1: Typical diagram of a single effect cycle configuration including the control layout

In order to identify the transfer function that can sufficiently represent the closed loop ABR dynamics, a simulation of the system of interest is performed. A number of step changes in the desired cooling capacity controller setpoint are performed in order to obtain the necessary response simulation data. The transfer function is estimated using the aforementioned data. In Figure 2a, the dynamic response of the closed loop of the ABR-control strategy pair is presented in comparison to the simulation results of the regressed transfer function.
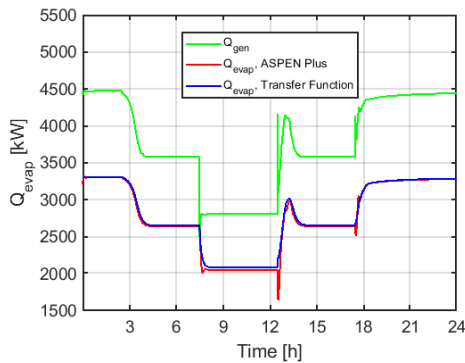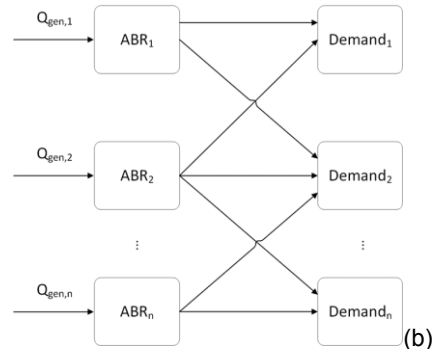
Figure 2: a) Comparison between closed loop simulation results (Q_{evap}, ASPEN Plus) and identified transfer function results (Q_{gen}, Transfer Function) and b) cooling network schematic representation

The non-linear, dynamic model simulation is in excellent agreement with the linear, dynamic, transfer function model simulation results. The transfer function model can predict both qualitatively and quantitatively the non-linear model response to the setpoint tracking simulation scenario. The identified, first order transfer function that presents 90.42 % goodness of fit based on the normalized root mean square criterion, is shown in Eq(1):

$$ABR(s) = \frac{0.09727}{s + 0.1323} \tag{1}$$

A first order plus dead time (FOPDT) transfer function is used to model the transport of the chilled medium, where its parameters are chosen based on the cooling medium flowrate and the distance between the ABR unit and the destination point. The FOPDT transfer function used to model cooling output transport is shown in Eq(2):

$$G(s) = \frac{Ke^{-s\tau_{TD}}}{\tau s + 1} \tag{2}$$

where K is the steady state gain, τ_{TD} the time delay and τ system's time constant.

2.3 Network modelling realisation

A district cooling network can be composed by a number of different ABR units strategically placed throughout the district of interest (Figure 2b). Each unit can take a different kind of heat input e.g., gas fired, solar energy, etc based on available resources. The availability of the energy resources depends on the inventory and storage planning, on the weather conditions and can vary over time (e.g., solar irradiation). In the current work, ABR heat input is considered to be provided by a gas burner (one for each unit) and as such the availability of the energy source is considered constant and able to satisfy the scenario under consideration.

The cooling demand of each end-user may vary with time, both daily and seasonally. Demand profiles can be estimated based on historical trends, weather forecasts and strategic planning and will be considered as input information for the decision support tool. Demand may change deterministically if known demand profiles are imposed in the system or stochastically as demand may fluctuate randomly. A schematic of the super-structure and the multiple interacting levels in a district cooling network under consideration is shown in Figure 2b. The number of chillers, number of end-users and the pattern of the interconnection between them can change according to the needs of each case study.

3. Scheduling of ABR network - Optimisation framework

The optimal operating conditions for the entire network over a time horizon determine the distribution of energy activities in a way that facilitates both the satisfaction of the demand and the minimisation of the operating costs. The time interval used for the simulation of the network dynamic behaviour is selected so that the system dynamics and interactions are properly described.

3.1 Mathematical formulation

This specific mathematical problem (Eq3) involves the minimisation of the cost function J that depends on the state, output, and manipulated variables, $(x(t), z(t), u(t))$ and variables associated to the realisation of the disturbances and demand scenario parameters, $(w(t))$. The optimisation problem is subject to the differential and algebraic equalities that describe the physico-chemical process, (f, h), and the inequality constraints that define the process operating region, (g), both determining the feasibility space.

$$\underset{u(t)}{\text{Min}} J(x(t), z(t), u(t), w(t))$$

$$f(\dot{x}(t), z(t), x(t), u(t), w(t)) = 0 \tag{3}$$

s.t.: $\quad h(x(t), z(t), u(t), w(t)) = 0$

$$g(x(t), z(t), u(t), w(t)) \leq 0$$

The decision variables set $(u(t))$ includes all operating condition variables, related to energy resource and cooling load allocation. Two types of performance indices are used for the evaluation of the dynamic operation performance of the process. The first type is related to the energy resources minimisation, whereas the other is related to setpoint tracking ability:

$$J = W_1 \sum_{k=1}^{N_t} \sum_{i=1}^{N_{ABR}} Q_{gen,i,k} + W_2 \sum_{k=1}^{N_t} \sum_{j=1}^{N_{ABR}} \sum_{i=1}^{N_{site}} (Q_{evap,j,k} Ratio_{i,j,k} - Q_{site,i,k})^2 \tag{4}$$

where N_t is number of discrete time intervals of dynamic simulation, N_{ABR} the number of ABR units employed, N_{site} the number of different demand sites needed to be served, $Q_{gen,j,k}$ is the j-th ABR unit heat input at time instance k, $Q_{evap,j,k}$ is the j-th ABR unit cooling production at time instance k, $Ratio_{i,j,k}$ is the percentage of cooling produced by j-th ABR that is directed to the i-th site at each time instance k, $Q_{site,i,k}$ is the i-th site cooling energy requirements at time instance k, and J is the value of the objective function.

In addition to the physico-chemical process related constraints, a number of algebraic constrains that define the feasibility region are imposed. These constraints are related to the maximum and minimum values of all design vector variables. For instance, ABR heat input can vary between zero and a maximum capacity value.

3.2 Implementation details

The case study presented in this work is a complex case where three ABR systems are used in order to satisfy the cooling demand of three end-users connected to the DC network. The first and second ABR are arbitrarily chosen to be connected to the first and second end-users. The third ABR is connected to the second and third end-users. The time delay of each interconnection between ABR and end-user is presented in Table 1. The demand profile of each customer is presented in Figure 3a, depicted with dashed lines. The time horizon for which the mathematical problem is solved is a daily variation equal to 24 h.

Table 1: Arbitrarily chosen time delay at each interconnection between ABR and end-user for the case study

	End-user 1	End-user 2	End-user 3
ABR 1	1.8	3.6	-
ABR 2	5.4	1.8	-
ABR 3	-	7.2	3.6

4. Results and discussion

The 1st and 2nd ABR unit can provide the 1st and 2nd demand site with cooling effect. The 3rd ABR unit can provide cooling effect to the 2nd and 3rd demand site. The decision variables are each ABR heat input and each ABR cooling output split ratio per hour (e.g., the 1st ABR is connected to both 1st and 2nd end-users). Having 3 ABR units, a 24 h time horizon and 2 types of decision variables per ABR unit per hour the total number of decision variables adds up to 144 in total. Optimisation results are presented in Figure 3 and Figure 4.

The cooling demand of each site is depicted in Figure 3a with red, blue and green dashed lines. The first site appears to have a maximum demand of 100 % of the nominal cooling capacity between 14:00 and 15:00. However, the overall cooling demand of all three end-users is never higher that the nominal capacity of all three ABR units together and as a result, the ABR are able to satisfy the demand of all end-users at every point. The operation optimisation results are able to satisfy cooling demand in all cases with small deviations and small overshoots as well. The produced cooling effect (continuous red, blue and green curves for each ABR) as well as the energy resource utilized (dashed red, blue and green lines for each ABR) are presented in Figure 3b. Heat resource utilisation level changes every hour and is manipulated by the optimisation framework such that the desired cooling effect in all end-users is satisfied.
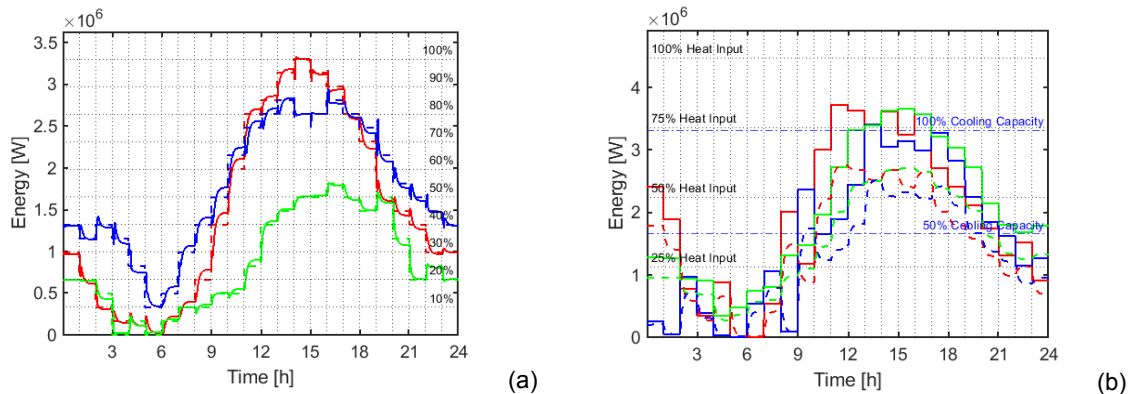

Figure 3: Case study: a) cooling effect delivered at each end-user compared to each demand profile and b) energy resources utilisation and dynamic responses of cooling effect produced by each ABR unit

In Figure 4, the cooling input at each end-user is analysed. More specifically, Figures 4a, 4b and 4c refer to end-user 1, 2 and 3. Red, blue and green coloured bars are cooling provided by the 1st, 2nd and 3rd ABR unit. The 1st end-user takes cooling from both the 1st and 2nd ABR units, the 2nd end-user from all ABR units. The 3rd end-user receives cooling from the 3rd ABR unit only. The produced cooling effect from each end-user is allocated based on the optimization framework (ratio). The same priority is given to each interconnection pathway, and as such no ABR saturation is observed.
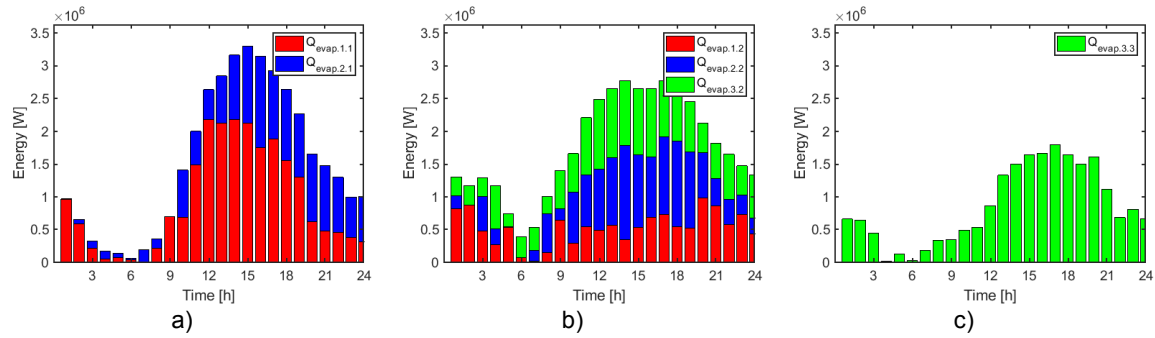
Figure 4: ABR cooling effect allocation to each end-user

5. Conclusions

An operation optimisation framework for the DC network of multiple ABR and multiple end-users with a number of interconnection options has been developed. Reduced order modes, regressed from non-linear ASPEN Plus Dynamics model results, are utilised in the framework in order to minimise the computational effort for solution. The predictive ability of the reduced order mathematical models is shown to be quite satisfactory (90.42 % goodness of fit). Unlike similar studies, the employment of the actual dynamic models of the cooling production unit enables the more precise measurement of the customer satisfaction level, based on which the optimal operation scheduling is performed. Results of the optimisation framework include the determination of the optimal allocation of produced cooling from each ABR unit at each end-user present in the DC network in such a way that cooling demand is always satisfied. Although the cooling capacity of some of the end-users is higher than that of each ABR maximum capacity (specifically during hot midday hours), the interconnection of the ABR units and the ability to serve more than one end-user enables for the maximum cooling satisfaction possible. The optimisation algorithm is able to allocate cooling effect from alternative routes in order to satisfy the cooling demand as soon as possible despite severe demand variability and by taking into account the DC network topology (distance between each ABR and its respective interconnected end-users). This work will be extended towards the evaluation of the performance of an existing DC network in Qatar, where the increased DC network complexity, the alternative cooling production units (e.g., VCR) and the energy source availability fluctuations will be taken into account.

Acknowledgements

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