Optimising a Waste Heat Recovery System using Multi-Objective Evolutionary Algorithm

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ABSTRACT

A waste heat recovery system (WHRS) on a process with variable output, is an example of an intermittent renewable process. WHRS recycles waste heat into usable energy. As an example, waste heat produced from refrigeration can be used to provide hot water. However, consistent with most intermittent renewable energy systems, the likelihood of waste heat availability at times of demand is low. For this reason, the WHRS may be coupled with a hot water reservoir (HWR) acting as the energy storage system that aims to maintain desired hot water temperature T_d (and therefore energy) at time of demand. The coupling of the WHRS and the HWR must be optimised to ensure higher efficiency given the intermittent mismatch of demand and heat availability. Efficiency of an WHRS can be defined as achieving multiple objectives, including to minimise the need for back-up energy to achieve T_d, and to minimise waste heat not captured (when the reservoir volume V_{res} is too small). This paper investigates the application of a Multi Objective Evolutionary Algorithm (MOEA) to optimise the parameters of the WHRS, including the V_{res} and depth of discharge (DoD), that affect the WHRS efficiency. Results show that one of the optimum solutions obtained requires the combination of high V_{res}, high DoD, low water feed in rate, low power external back-up heater and high excess temperature for the HWR to ensure efficiency of the WHRS.

1. INTRODUCTION

Renewable energy systems are often intermittent in nature, and often do not produce sufficient energy at times of demand. Because of this, they are often coupled with an energy storage system (ESS) in order to optimise the utilisation of the generated energy. The ESS ensures that if the energy is generated at a time of low demand, it can be captured and stored for use when energy is in demand [13].

Optimal sizing and operation of the ESS is an ongoing subject of investigation. It is important because:

1. insufficient sizing of an ESS will result in the energy generated from renewables not being fully captured.

2. insufficient sizing, repeated fully discharging, or high depth of discharge (DoD) will reduce the lifetime of the system [12], [18], [25], [27], although there are technologies that can mitigate this.

3. over-sizing results in a high cost of operation [27].

These issues are commonly seen when solar or wind power generation is coupled to an ESS. They are also observed in waste heat recovery systems (WHRS). In an WHRS, the renewable energy is in the form of waste heat, and the ESS is realised by a hot water reservoir (HWR). Depth of discharge (DoD) for a WHRS is the minimum water level that must be maintained by the HWR when hot water is in demand. A further issue with the WHRS, is that when the DoD of the WHRS is too high, the time taken to bring the water temperature and volume up to the demand requirements may be too long. This will result in the need for external heat to meet the demand within time.

Be it homes, commercial buildings or process industry, if waste heat is captured and used to meet the hot water demand, this may help reduce the cost of energy usage [16], [23]. Examples of such are the works presented in [9], [19], [20], [21], which incorporate heat pumps to maximise the energy recovery from waste heat.

This paper describes the use of a multi-objective evolutionary algorithm (MOEA) to maximise the energy recovered from waste heat for hot water usage in an WHRS. The MOEA is used to optimise the process integration—that is,

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to optimise the parameters to achieve efficient heat recovery and usage. According to the literature, the optimisation of process integration tends to be performed by human expert analysis of monitored data and thermodynamic models [5], [17], [15], [28]. An MOEA was chosen to overcome limitations of these methods, allowing exploration of a wider range of potential solutions. The potential utility of an MOEA for solving this problem is also indicated by the success of existing research where methodology has been applied to the optimisation of solar and wind-coupled ESS.

The effectiveness of heat energy recovered is directly affected by the temperature difference (ΔT) between the heat source (from waste heat) and its sink (water in the HWR). ΔT is also affected by the flow rate of the source and sink through the heat exchanger (or desuperheater), the volume of the HWR [5], [9], [15], [28], as well as heat loss. MOEA was chosen to optimise the multi-parametric solutions for the WHRS through metaheuristics.

This paper is further divided into five sections. Section 2 provides a brief description of the WHRS that aims to reuse waste heat to provide hot water at the demanded temperature T_d. There are few studies describing the optimisation of the WHRS operations. However, because of the similarities of WHRS and that of the ESS, the studies conducted in optimising the ESS using MOEA were used as references. Section 3 provides a brief description of such studies. Section 4 describes the model, simulation and the experiments for optimising the WHRS. Section 5 indicates the results from the optimisation. Section 6 concludes the paper.

2. WASTE HEAT RECOVERY SYSTEM

The refrigeration process is an example of a system that produces waste heat. Others examples include, combined heat and power systems (CHP) and large computing systems (server farms and computers). In the process industry, specifically in food production and manufacturing, large refrigeration units are used to chill processed food. These refrigeration systems can produce large volume of waste heat. The waste heat captured can provide sufficient energy to produce hot water.

If a WHRS is placed before the condenser of the refrigeration system, for example a heat exchanger (i.e. a desuperheater), waste heat can be captured and used to increase the temperature of water. The integration of the desuperheater with refrigeration plant is illustrated in Figure 1.

To ensure sufficient heat is captured, the difference between the temperature of the water and that of the refrigerant (ΔT) should be large. Ideally, water from a mains supply will normally provide that large temperature difference, and is sufficient to ensure heat energy capture. This is ideal if the demand of hot water is in sync with when the waste heat is generated. However, like most renewable energy systems, waste heat is often generated when the demand is low. The use of hot water in food processing plant is required for cleaning (clean-in-process (CIP), washdown), and this occurs at the beginning of the process when the need for refrigeration is lower and lesser waste heat is generated. This for example is as indicated in Figure 2, which shows water usage for CIP peaking when the energy used by the compressor in a refrigeration plant is not. The compressor is responsible for pressurising and increasing the temperature of the refrigerant, which maximises the release of heat from the refrigerant to the environment.

To ensure the efficiency of the WHRS, a number of parameters should be optimised. The parameters attributed to, and not limited to, the HWR volume integrated with the WHRS and how the water is used.

2.1 Hot water reservoir volume

The hot water reservoir (HWR) must be maintained at the desired temperature when hot water is demanded. Figure 3 shows the functions which represent the relationships between the reservoir volume versus that of the amount of heat captured (including the amount of heat not captured and lost to the environment), the intersection point on the graph indicates the desired volume for the reservoir. To find this intersect point, that is to find the optimal reservoir volume is an optimisation problem.

The y-axes in Figure 3 are among the objectives which are to be minimised by MOEA. For the right y-axis, the objective is to minimise the need for back-up energy provider (i.e. backup heater in Figure 1) for the HWR.

2.2 Levels of operation

2.2.1 Water volume levels

Existing hot water systems most commonly operate to ensure that T_d is available when required, and that the level in the reservoir is kept above the minimum level when in demand to prevent dry out. If the system is incorporated with WHRS, a low minimum level may result in the need for external energy to bring the water temperature up to T_d and the volume required when in demand. This need may arise when the time difference between the demand is less than the time taken for the WHRS alone to meet T_d and the volume required. Therefore, the minimum level maintained when discharge should be sufficient to ensure that when the water is replenished from the water mains (to bring the volume up to the desired level V_{max}), the water temperature is constantly maintained at a high temperature T_{hw} with minimal injection of heat from the external energy source.

If the maximum water volume (V_{max}) of the HWR is kept low, this may result in heat energy wastage. This is because no heat is needed as T_{hw} is met and V_{max} is reached.

2.2.2 Temperature levels

Whether there is demand for energy, the HWR is in idle, or the hot water is recycled through the desuperheater to capture heat waste, there will always be loss of energy to the environment. This is because of the temperature difference between the contents of the reservoir and its surroundings. Therefore, when no heat waste is available, there is the likelihood of a drop in temperature of the water in the HWR. Consequently, to ensure that no external heat is required when in time of need, an excess of heat has to be captured when it is available. In preparation for idle, the water has to be kept at a higher temperature T_{hw} (1) than what it is later demanded (T_d). This is to ensure the T_d is met, despite the loss of heat to the environment.

$$\Delta T_{max} = T_{hw} - T_d \tag{1}$$

The excess heat captured should not be excessive. If this occurs, rapid cooling of the water will be required when it is needed, either through refrigeration (i.e. external energy in the form of electrical power to reduce the temperature)

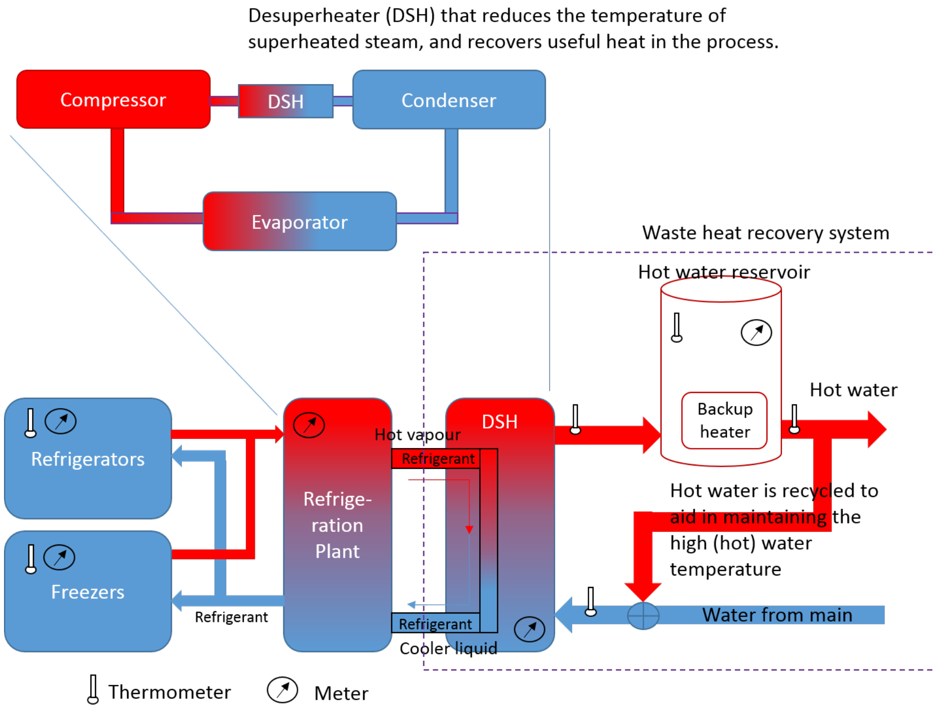

Figure 1: An example integration of a WHRS (the desuperheater or heat exchanger) with a refrigeration plant.

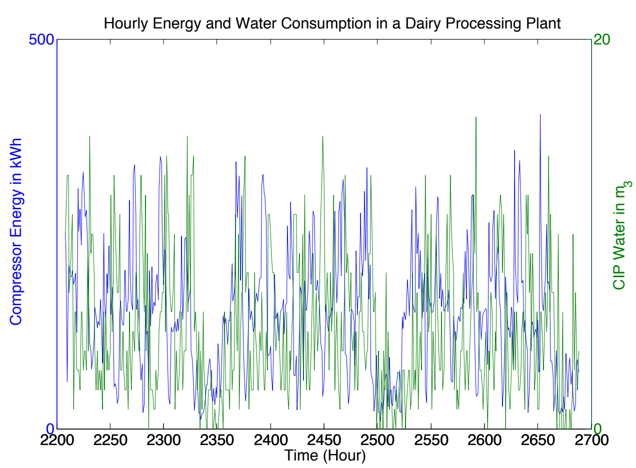

Figure 2: 20 days of energy and CIP water usage at a dairy processing plant in September 2015. Peaks for the two system are at the opposite of each other.

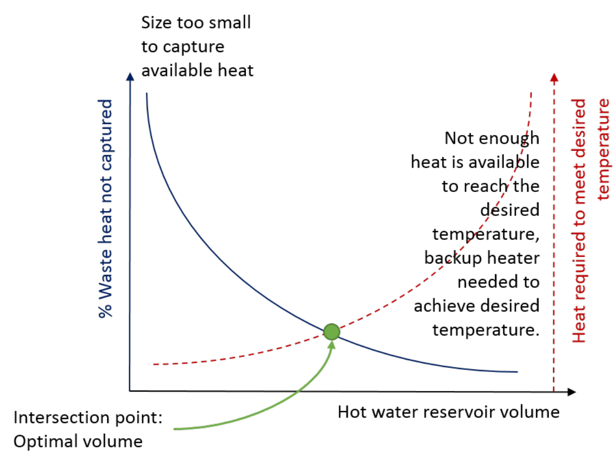

Figure 3: How two mutually exclusive parameters influenced by the volume of the hot water reservoir.

or water from the mains (extra cost). Preventing the need for coolant is the objective to find the pinch point (ΔT_{max}) in process integration.

It is essential that the system optimise both the water volume level of the reservoir and the temperature level for which the reservoir needs to reach if there is idle time between waste heat availability and demand. These parameters are to be evolved using the MOEA. A detail description of them can be found in Section 4.

3. RELATED WORK

Efficient process integration is highly dependent on optimisation. For the combination of ESS and renewables, optimisation of the DoD and its size are required so that the charging and discharging of the ESS will not affect the lifetime of the ESS itself and the grid it is connected to.

Similar constraints apply to a WHRS. The HWR operations and conditions are to be optimised. This is to ensure that the volume of water in the HWR is at the temperature T_{hw} and capacity V_{max} that are required by the demand.

There are a number of studies related to the optimisation of the ESS sizing and DoD; however, only a few concern

WHRS. Since these two systems have similar functions and constraints, the conclusion from the latter studies can aid in the former optimisation.

The authors of [29] describe the use of MOEAs to optimise the battery parameters for use in stand alone microgrids. The parameters are the SoC battery set point, the excess power set point of renewable energy that the batteries allow charging, and the charging power set point of batteries when the diesel generator operates. The optimisation is performed with the objective of minimising the cost of power generation in line with the minimisation of cost of the battery life loss. They state that the higher the state of charge (SoC) of the battery, the lower the life loss cost of the battery, with the MOEA providing a pareto-front of optimised solutions. Similar works are described in [11], [27], [6].

The authors of [28] analysed the WHRS operations in dairy process industry using expert analysis. They analysed data from eight process plants using thermodynamic models of the WHRS and pinch analysis. Their analysis showed that more heat can be recovered when utilising variable temperature storage (VTS) because VTS allows for higher ΔT at the heat exchanger, enabling for more heat recovery, in comparison to constant temperature storage (CTS). Other similar works are presented in [17], [15], [4]. These methods of analysis are time consuming and require high fidelity data and model, which can be difficult to obtain [16]. Since the output reliance on human expert, the optimisation search space is limited, which in turn may lead to sub-optimal solutions. Therefore, metaheuristics are more advantageous in performing such analysis.

4. MODEL AND SIMULATION

MOEA searches for Pareto-optimal solutions found from maximising or minimising the multiple objective functions. Each objective function is evaluated as an individual component of optimisation, neither summed nor averaged to form a single value. This provides flexibility, with the Pareto-optimal front providing a choice of solutions to the installer that explore different trade-offs in the design space. Because of this, MOEAs therefore were chosen for optimising the design and operational parameters of the WHRS.

To evaluate the capabilities of the WHRS, a simulation model was constructed. This model simulates the temperature changes in the HWR given the discharge temperature of the refrigerant [24], the demand of the hot water, and the energy lost to the environment (since 100% insulation is impossible). This is depicted in Figure 4.

Based on the example indicated in Figure 2, the first half of the simulation is simulated so that waste heat is at its maximum capacity when there is no demand, and with similar time intervals (the first 5 work days or at $0s$ to $4.32\times10^5 s$ in Figure 4). To add variability, in the second half of the simulation (the next 5 work days or at $6.048\times10^5 s$ onwards), the frequency of the refrigerant discharge was doubled with its intervals reduced by half of that of the hot water demand. The demand hot water flow rate is $2kl$/hr or $0.5556 l/s$. The model was simulated in Simulink® using thermodynamics equations. The MOEA was implemented in Matlab®.

The Non-Sorting Genetic Algorithm NSGA-II was used. This algorithm has been successfully used in previous studies of ESS optimisation, outperforming other MOEAs in terms of hypervolume and individual optimised solutions [6]. As we have noted, there are strong similarities between ESS and WHRS operations.

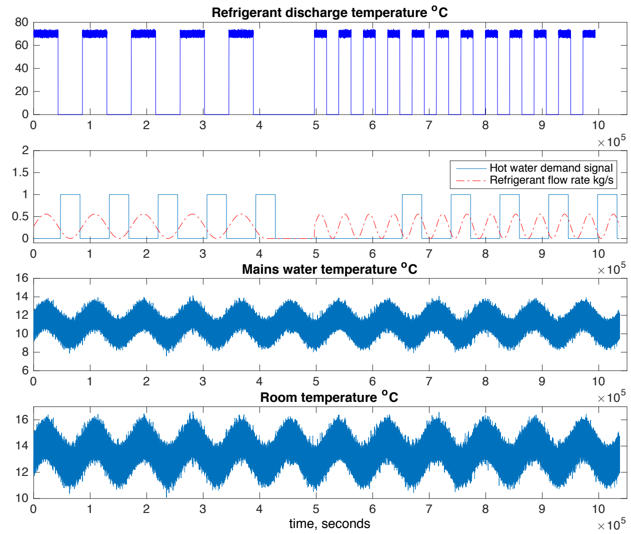

Figure 4: The simulation parameters.

Values for the NSGA-II parameters are those indicated in [10]: mutation probability = 1/number of evolved parameters; and distribution index for crossover = 20. Distribution index for mutation = 100, for population size = 200. $T_d = 60^o$C, a typical hot water temperature required for CIP. V_{res} and T_{hw} are initialised with the evolved V_{max} at T_d. Given that the simulation of the WHRS and HWR operations are computationally expensive, only one run of NSGA-II was performed and analysed, up to 77 generations.

4.1 Evolved parameters

The parameters evolved were:

1. the maximum volume of the water reservoir V_{max},

2. the minimum volume of the water that must be maintained when there is demand for hot water, V_{min}. If expressed as a percentage, this will be given by (2). The depth of discharge is given by (3),

$$V_{min} = (1 - (\text{DoD in }\%/100)) \times V_{max} \tag{2}$$

$$\text{DoD} = (1 - V_{min}/V_{max}) \times 100\%) \tag{3}$$

3. maximum temperature of the water in the reservoir T_{hw} (1), when the reservoir acts as a heat storage,

4. the maximum flow rate of the water into the desuperheater (DSH), $\dot{v}_{max}$, and

5. the maximum power for the backup heater, P_{max_b}.

The latter three parameters are evolved to ensure the pinch point (ΔT) is met [3], [14].

Table 1 lists the limits for the evolved parameters. The limits were added to bound the search space and to speed up the convergence of the Pareto-optimal front.

Table 1: Limits for the evolved parameters.

Parameter	min	max
Maximum volume of water reservoir, V_{max}	1.0kl	50.0kl
Minimum volume that must be observed in % of the maximum volume (DoD)	10%	100%
Maximum ΔT_{max} (1)	0°C	98°C - T_d
Maximum water flow into the DSH $\dot{v}_{max}$ (l/s)	0.5l/s	1.0l/s
Maximum power for the back-up heater P_{max_b}	100kW	1000kW

When there is no demand for hot water and the water level is at V_{max}, the waste heat is used to bring the water temperature higher than demanded, up to T_{hw} (1). If the volume of the reservoir $V_{res} < V_{max}$ when not in demand, the volume of water is replenished from the mains water source, with the mains water temperature indicated in Figure 4. During this time, the back-up heater is not used. There are two reasons for this: firstly, given that the WHRS is a slow reacting system and the back-up heater is a faster reacting one, the back-up heater will become the primary heat source to the reservoir, bringing the temperature in the water reservoir up to T_{hw} faster than the WHRS. This, in turn results in the redundancy of the WHRS. This issue is often observed in similar slow reacting renewable energy systems, for example, ground source heat pumps used for space heating [7], [22], [2].

Secondly, the use of a backup heater creates a reservoir with constant temperature storage (CTS). A number of studies [8], [15], [17], [26], [28] show that variable temperature storage (VTS) outperforms CTS in heat recovery. This is because VTS allows for higher ΔT at the desuperheater, enabling for more heat recovery.

When in demand, V_{min} must be kept (2). When $V_{res} < V_{min}$, the water in the HWR is replenished from mains water supply at the constant rate of $\dot{v}_{max}$ and is heated by the back-up heater with the constant power of P_{max_b}.

4.2 Objective functions and constraints

Six objectives were used to guide the optimisation:

1. to minimise the cost of external (added) energy, typically from non-renewables. The added energy is required when the heat captured by the reservoir is insufficient to meet the demand. This will occur when the volume of the reservoir is too large.

2. to maximise the savings when using the WHRS. When in use by MOEA, to minimise:
   1 - ((total energy usage without WHRS - total energy usage with WHRS)/total energy usage without WHRS).
   More savings can be achieved when a larger volume is used and/or the DoD is low. This is because any top-up of water to its maximum reservoir volume (V_{max}) will not result in significant drop of the water temperature. Therefore, less external energy is required.

3. to minimise the heat waste not captured. This can occur when the volume of the reservoir is too small, and T_{hw} and V_{max} are met at times when there is no demand for the hot water. Heat waste will not be captured when ΔT between the water and that of the refrigerant is near equilibrium. Heat waste not captured is counted when water heated from the heat waste is not added into the hot water tank.

4. to minimise the temperature difference when the temperature of the HWR exceeds $T_d + 1^o$C[1] when the hot water is in demand.

5. to minimise the temperature difference when the temperature of the HWR is below T_d - 1^oC when the hot water is in demand.

6. to minimise the volume of water exceeding V_{max}.

The first objective will aid in achieving the target to reduce the carbon gas emission by at least 80% from the 1990 level by 2050 [1]. The second and third objective functions, however, ensure the design chosen will help in achieving the commitment of the 2015 UN Climate Change Conference to limit the global temperature rise to as little as above 2^oC, by reducing the amount of waste heat emitted. Objective 1 can be achieved by having a small V_{max}; however, objectives 2 and 3 can be benefited when V_{max} is larger. The use of an MOEA helps to find the optimised sizing for V_{max} and to determine which parameters will obtain the best WHRS operations. Objectives 4–6 are to ensure that the design and the demand requirements are met. The constraint implemented is $T_{hw} \leq 100^o$C.

5. RESULTS

Table 2 shows the values obtained for the objective functions when the minimum objective value for each objective function is evaluated. These values are obtained from the final generation (generation no. 77[2]). Their corresponding evolved parameters are listed in Table 3.

The spread of the evolved parameters and their external energy used with the WHRS and the savings which can be achieved are indicated in Figure 5. Results show that for one of the objectives, to minimise external energy used by the WHRS, the following combination is ideal:

1. Large volume for the HWR is required. Large volume is when $V_{max} > 25kl$.

2. DoD must increase if V_{max} is to be decreased. To achieve maximum savings, DoD is best high, approximately 83% with large V_{max}, $V_{max} \approx 49kl$.

3. P_{max_b} and $\dot{v}_{max}$ are best at their minimum values, with $P_{max_b} <$ 500kW and $\dot{v}_{max} < 0.6l/s$, provided that the DoD is high (DoD > 50%);

4. $30^o\text{C} > \Delta T_{max} > 20^o\text{C}$ with high DoD (DoD > 60%)

The combination above also resulted in 0% of waste heat not recovered.

Small $\dot{v}_{max}$ enables for higher increase in the water temperature that exits the desuperheater, but at smaller rate of filling of the HWR to V_{max}. Fast filling of the HWR at high temperature can result in waste heat not being captured.

The Pareto-optimal front provides variety of combinations that were optimised by the MOEA. This gives the choice for the WHRS's design and operational parameters.

[1]Ideally much larger differences are tolerable ≈ ±3°C; but

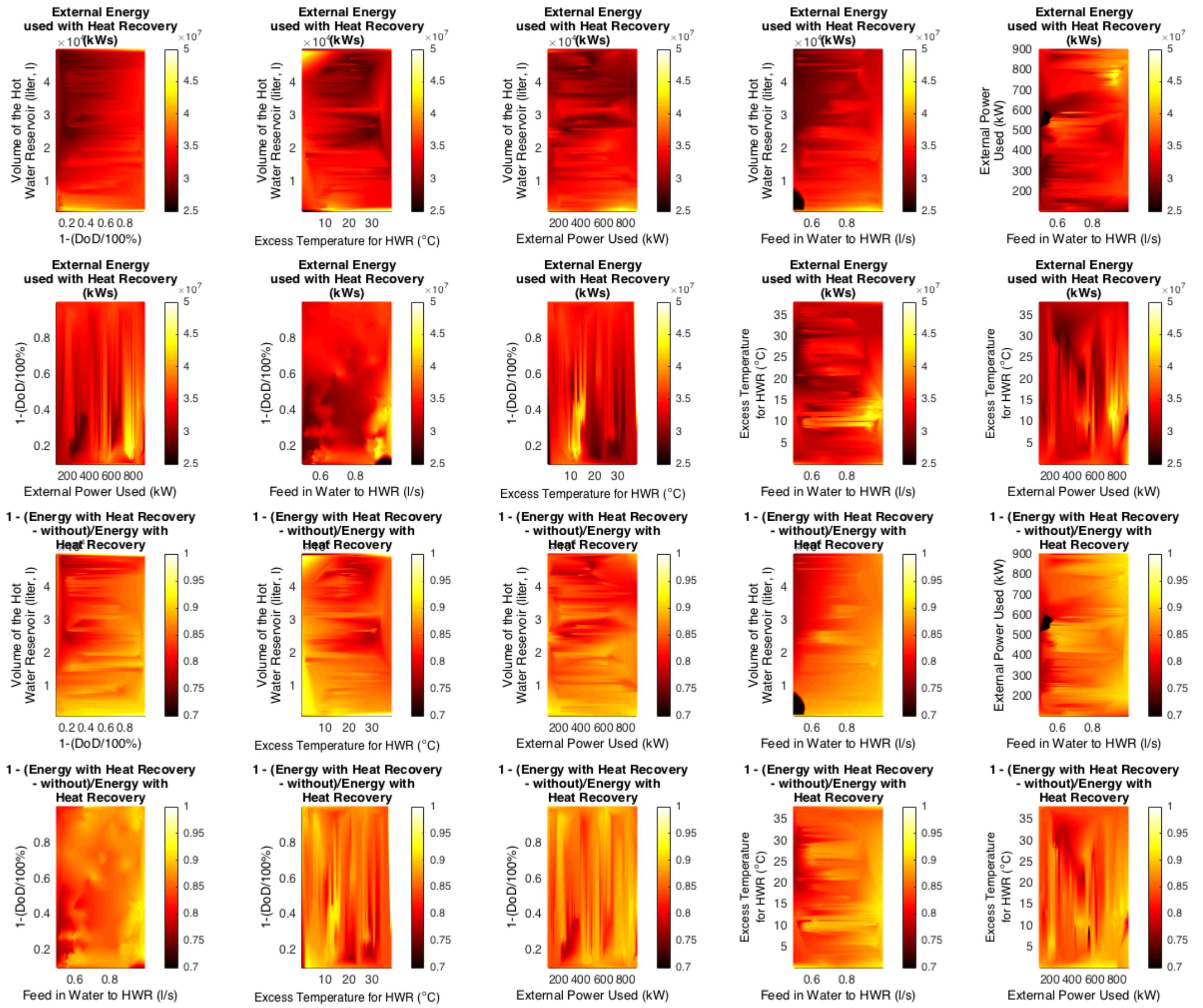

Figure 5: The spread of the external energy used and savings achieved, approximated using the combination of the evolved parameters from the 1^{st} to 3^{rd} generations and the last 10 generations. The last generation is generation no. 77.

6. CONCLUSION

This paper describes the outcome of investigations into the use of an MOEA for optimising the process operation of a waste heat recovery system (WHRS) coupled with a hot water reservoir (HWR). A WHRS is an example of an intermittent renewable process, which recycles waste heat into usable energy. As an example, waste heat produced from refrigeration can be used to provide hot water. However, consistent with most intermittent renewable energy systems, the likelihood of waste heat being available at times of demand is low. For this reason, the WHRS is coupled with a HWR acting as the energy storage system that aims to maintain T_d at time of demand. The coupling of the WHRS and the HWR must be optimised to ensure higher efficiencies given the intermittent mismatch of demand and heat availability. Efficiency of a coupled WHRS and HWR can be defined as achieving, among others, two main objectives: to minimise the need for back-up energy to achieve T_d at time of demand, and to minimise waste heat not captured. Results show that a combination of large V_{max} ($V_{max} \approx 50kl$), high DoD (DoD $\approx 84\%$), low P_{max_b} ($P_{max_b} < 500$kW), low $\dot{v}_{max}$ ($\dot{v}_{max} < 0.6l/s$) and high ΔT_{max} (20^oC $< \Delta T_{max} < 30^o$C) are required for an efficient coupled operation of the WHRS and HWR to achieve one of its objective of a minimum external energy used. The Pareto-optimal fronts provides other combinations among the optimised solutions.

for this analysis, we are testing the capabilities of the MOEA to find the parameters meeting the extreme conditions.

[2]The objectives values and the evolved parameters converged after 40th generation

7. ACKNOWLEDGMENTS

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Table 3: Evolved parameters at the final generation (generation no. 77).

	V_{max}	DoD %	ΔT_{max}	P_{max_b}	$\dot{v}_{max}$
Min. external energy used	49.552kl	83.47%	21.1519^{o}C	489.5203kW	0.5022kgs^{-1}
Max. savings achieved	49.552kl	83.47%	21.1519^{o}C	489.5203kW	0.5022kgs^{-1}
Least max. temperature difference when below T_d	39.035kl	54.07%	12.3595^{o}C	126.2680kW	0.6208kgs^{-1}
Least max. temperature difference when above T_d	24.498kl	9.64%	0.4549^{o}C	100.8679kW	0.6573kgs^{-1}
Least max. weight exceeding $m_{wt_{max}}$	6.6045kl	73.18%	26.9278^{o}C	188.073kW	0.5883kgs^{-1}
Min. % heat not recovered	1.5290kl	81.89%	11.1020^{o}C	769.6736kW	0.9276kgs^{-1}

Table 2: Objective values for the final generation (generation no. 77).

	External energy used P_{max_b}	Savings achieved	Max. temperature difference when below T_d	Max. temperature difference when above T_d	Max. weight exceeding	% heat not recovered
Min. external energy used	2.7345×10^7 kWs or 7.5957 MWh	23.88%	0^{o}C	2.0493^{o}C	29.5103kg	0%
Max. savings achieved	2.7345×10^7 kWs or 7.5957 MWh	23.88%	0^{o}C	2.0493^{o}C	29.5103kg	0%
Least max. temperature difference when below T_d	2.8979×10^7 kWs or 8.0496 MWh	19.46%	0^{o}C	2.4802^{o}C	31.6026kg	0%
Least max. temperature difference when above T_d	3.4424×10^7 kWs or 9.5623 MWh	10.68%	3.5134^{o}C	0^{o}C	37.4935kg	0.2639%
Least max. weight exceeding $m_{wt_{max}}$	3.3932×10^7 kWs or 9.4256 MWh	13.37%	0^{o}C	7.4697^{o}C	9.3748kg	0%
Min. % heat not recovered	4.5580×10^7 kWs or 12.6610 MWh	12.34%	6.2114^{o}C	38.5096^{o}C	54.3653kg	0%