Energy Modeling Framework for Optimizing Heat Recovery in a Seasonal Food Processing Facility

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Abstract

Societal, cultural and economic factors are driving food processors to reduce energy consumed per unit mass of food. This presents a unique problem because time variant batch processing using low to medium grade heat is common in food production facilities. Heat recovery methods may be implemented by food processors to reduce energy consumption; however, temporal variance in the process and utility flow require the development of a robust, easily implemented energy model to accurately determine system effectiveness and economic incentive. A bottom-up modular computational framework is proposed to model the energy consumption of a cannery. The model predicts that the cannery will require 612 kJ gas/kg product produced, which is within the ranges provided in previous literature. Results show that adding a globally optimized indirect heat recovery system will reduce the gas consumption by 6% annually. The proposed framework, used here to represent a cannery, may be adapted to many different types of food processing facilities. With a clear picture of energy consumption by device, and the ability to predict the impact of process modification or heat recovery, plant-level energy usage for food processing may be significantly reduced.

Keywords: Energy Efficiency, Food Industry, Heat Recovery, Optimization, Simulation

Nomenclature

A	Area
$Approach$	$T_{w,out} - Twb_{a,in}$
C	Fluid capacity
Ceq	Nonlinear Constraint Equation
CT	Cooling tower
c_p	Specific heat at constant pressure (per unit mass)
Den	Density
D_h	Hydraulic diameter
E	Effectiveness
F	Correction Factor

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h	Enthalpy (per unit mass)
k	Thermal conductivity
HX	Heat exchanger
$\dot{m}$	Mass flow rate
N	Number of increments used for discretization
NN	Neural Network
N_s	Number of plates
NTU	Number of transfer units
P	Pressure
pws	Saturation Water Vapor Pressure
Pr	Prandtl
R	Heat Capacitance Ratio
$recirc$	Flowing thermal fluid
$Range$	$T_{w,in} - T_{w,out}$
Re	Reynolds
RH	Relative humidity (as a percentage)
s	Plate spacing
T	Temperature (dry bulb, or bulk conditions)
Twb	Wet bulb temperature
U	Overall heat transfer coefficient
V	Volume
v	Specific volume
$\dot{V}$	Volumetric flow rate
Ws	Moist air saturation
η	Efficiency
ϕ	Relative humidity (as a fraction)
ω	Humidity ratio

Subscripts

a	Air
act	Actual
amb	Ambient
avg	Average
$brine$	Salt process water
can	Can full of product
c	Cold side
(d)	Desired, or design, value
da	Dry air
db	Dry bulb
e	exit condition
f	Liquid water (saturated)
g	Water vapor (saturated)
h	Hot side

hx	Heat exchanger
in	Inlet conditions
out	Outlet conditions
pw	Process water
$recirc$	Recirculation Circuit
s	Isentropic
sat	Saturation conditions
tw	Tower water
twr	Tower water return
tws	Tower water supply
w	Water
wb	Wet bulb
$zone1$	Cooker cooler heating section
$zone2$	Cooker cooler cooling section

1. Introduction

As consumers have become more interested in sustainable energy, efficiency is becoming a foremost concern for many food processing companies. So much so that leading food processing companies are voluntarily adopting measures to reduce the amount of energy it takes to process foods. To this end, forty-two companies, including some of the largest food processors, have partnered with the U.S. Environmental Protection Agency (EPA) to improve their energy efficiency as part of the Energy Star Food Processing Focus [1].

Many different technologies are used by and available to food processors to offset primary electrical energy consumption, such as photovoltaics and wind generation. Alternatively, electrical cost may be reduced by shifting power consumption to off-peak hours. Zhu et al. developed an energy model for a refrigerated food warehouse and proposed integrating energy storage, calculating that operating costs could be reduced by 18% [2].

However, natural gas accounts for 52% of the energy used in the US food manufacturing industry [3]. More specifically, natural gas to generate steam accounts for 65% of the energy use in a typical cannery or 1977 $\frac{kJ}{kg}$ of product produced [4, 5]. Steam is typically generated through fossil fuel combustion. Alternatives to fossil fuel have been studied, such as the anaerobic digestion of waste streams at canning facilities, and have been considered as a more sustainable means to produce steam. Hills presented real-world results from a 2-year laboratory digestion of tomato, peach and honeydew [6]. Raynal increased solid removals and methane production by using a two-stage anaerobic digestion [7]. Batstone investigated the impact that granule size has on methane production in brewery and slaughter house waste streams [8]. Most recently Zhang considered a three-stage anaerobic to increase methane production [9]. Another approach to reducing total energy use is to maximize the efficiency of steam production. Freschi and Giaccone assessed the effectiveness of maximizing the efficiency of fuel usage by optimizing a trigeneration system within the food industry [10].

Both practices reduce fossil fuel, although pollutants (CO_2, NOx, etc) are still produced during combustion.

Perhaps a more economical and reliable way to reduce on-site emissions is to simply use thermal energy more efficiently within the facility. In particular, heat recovery focused on reducing the plant's total steam consumption will have the largest effect on reducing local emissions. Wang estimated that recovering and reusing heat before it is lost to a heat sink can save 8.96-11.95% of the total industrial fuel use in British Industry [11]. Waste heat recovery systems in American food factories have also been studied.

Heat recovery systems have been widely studied. An in-depth literature review by Miro found that the study of waste heat recovery systems in the industrial sector began in the 1970's but not until 2006 was the field of much interest. Miro attributed the revised popularity due to increased environmental interest [12]. One common approach to capturing low-grade waste heat is to transfer excess heat to centralized thermal storage tanks [13]. Duscha and Masica [14] and Wojnar and Lundberg [15] estimated that recovering waste heat into a thermal storage tank and reusing the thermal energy could reduce energy consumption in American food factories up to 6%. However, the optimization and design of the central thermal transfer systems are typically based on pinch analysis, mixed integer linear programming, or some combination of these approaches. A critical review by Klemes et al describes the historical background of Pinch Analysis and Mathematical Programming for waste heat recovery system, sometimes called heat integration. Klemes et al proposed that Mathematical Programming is best suited for problems that consider multiple objectives and/or a high number of optimization variables [16]. Tokos used mathematical programming, specifically mixed integer linear programming, for optimizing waste heat recovery systems at a batch processing brewery [17]. More recently Lee et al. used mixed integer linear programming for optimizing the heat recovery system but extended the optimization to include operational scheduling. Lee et al. chose mixed integer linear programming because pinch analysis "may not be readily applied to cases with practical constraints on network design or cost consideration, are are incapable of handling time as a variable" [18].

A recent EU funded road-mapping project to promote the integration of energy efficiency in manufacturing found that an easy to implement cost calculation tool is required [19]. Ideally, the tool would make the "resource and energy-cost transparent to facility management" [19], which will allow managers to make informed decisions on plant construction and design. One such model has been developed by Herman [20]. Herman's work provides a flexible and dynamic simulation model that uses discrete events to calculate energy use over time. The framework proposed here builds on Herman's model, integrating stream to stream heat recovery evaluation to facilitate plant management insight into to cost implications of implementing low-grade heat recovery within their facilities.

A robust framework for evaluating and implementing heat recovery within a batch processing plant has been proposed by Miah [21]. The work in this paper describes the development of an easy-to-use simulation model integrating the techniques from both Miah and Herman.

This paper presents the development of a general purpose batch processing energy model with stream-to-stream heat recovery framework designed to give plant managers and system designers an efficient tool for use during facility design phase or operation to optimize plant energy utilization. The model is generalized by the development of a standard recipe input format and shift scheduler.

The model proposed is unique in that it extends the dynamic simulation to include utility generators such as boilers, cooling towers, and steam to hot water heaters. Utility generators may be modeled using conventional thermodynamic methods such as conservation of energy or through the use of neural networks. Neural networks (NN) are beneficial to the model because they may be implemented with little computational cost and without the need to represent the physics of heat and mass transport throughout the device. The methodology proposed in this work of using a (NN) to model cooling tower improves on previous energy models because it incorporates TMY3 weather data to more accurately reflect how seasonal weather changes impacts cooling tower efficiency. Recent energy models developed for the tomato paste processing industry assumed a constant cooling tower heat rejection efficiency [22].

The model's output data may be used to determine where heat recovery is feasible and to size a heat recovery system. Optimizing the heat recovery system in a batch processing plant is challenging due to the wide range of recipes, which impact the availability of excess heat. Here, an indirect heat recovery system is evaluated and optimized. A framework proposed by Henze [23] was modified to represent batch processing facilities. The optimization technique may be applied to any time-sensitive heat recovery system. Figure 1 presents a general block diagram that may be applied to any batch processing facility.

The framework developed here is then applied to a small seasonal, cannery as a case study, to demonstrate the use of the model. The results from the model are analyzed to determine any possibility for waste heat recovery. An indirect thermal storage system is proposed.

Finally, the proposed heat recovery system is analyzed for system payback because "To actually be applied a technology has to be economically competitive and attractive." [24].

In summary, the key contributions of this work are to:

- Expand the capabilities of existing model frameworks to include on-site utility generation
- Locale weather data is incorporated into the model to more accurately reflect season changes
- Reduce computational time by leveraging neural networks where practical
- Propose a standardized recipe format for batch processing facilities
- Provide a simulation model that may be easily modified to see the impact of plant operational schedule changes
- Illustrate the energy impact of heat recovery by implementing heat recovery within the system model

- Optimize the heat recovery system across a wide range of recipes
- Assess the economic feasibility of the heat recovery system

The novelty of this research is an energy model framework that is easily adaptable to different processes through the use of a standard recipe format and modularity. Additionally, the model leverages neural networks to reduce computational time where appropriate and integrates TMY3 weather data to assess the impact of seasonal weather changes on system efficiency. Lastly, the paper demonstrates how an optimization method originally developed for co-generation plants [25] can be applied to the food processing industry to optimize heat recovery systems. The developed model is unique in that the model encompasses a high-resolution energy model and state of the art mathematical programming optimization techniques. Finally, the optimal heat recovery system is implemented in the energy model to test the optimization results and see the impacts of heat recovery across the entire system.

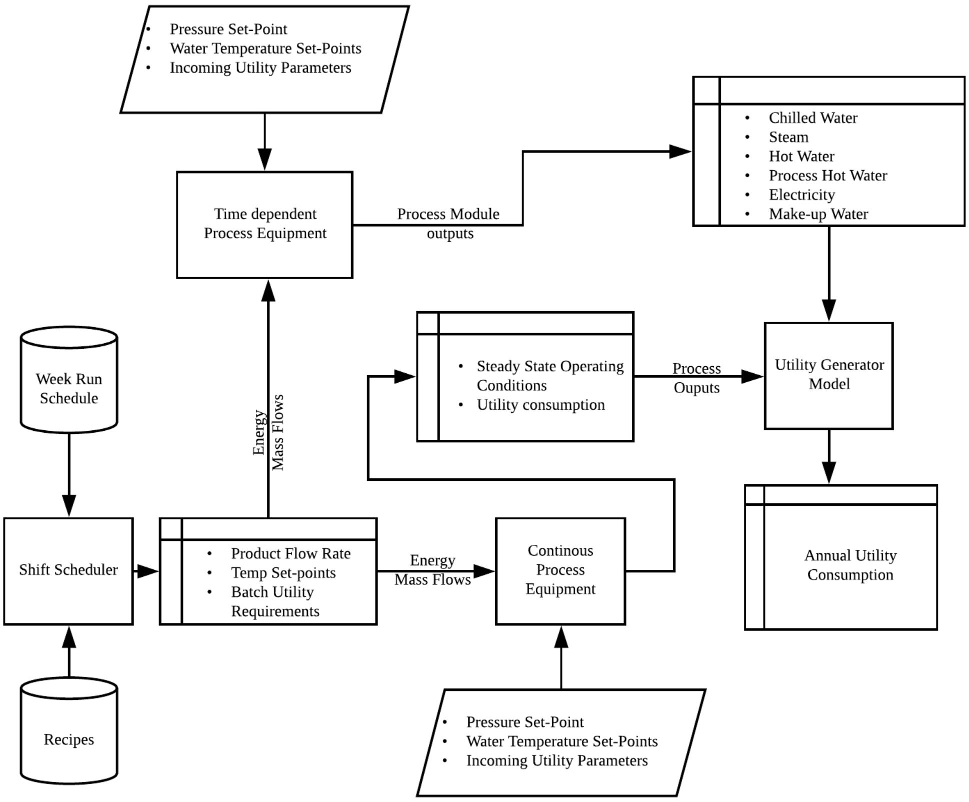


Figure 1: Generic Block Diagram

2. Methodology

2.1. General-Purpose Batch Processing Model Framework

The food processing industry involves a myriad of processes, products, and technologies. To develop an energy model that is useful across the various food processing industry sectors, we used a modular framework for constructing the energy model. The system energy model is comprised of the following primary modules: shift scheduler, process, and utility equipment.

Typically, food plants produce varying products throughout the year, sometimes changing products one or more times over the course of a day. Each product may be similar to others being processed or completely unique. Regardless of the size or complexity of the food plant, food processing requires that predefined steps are followed in order to repeatedly make consistent products. Each facility may use a proprietary control philosophy but the steps must always follow a logical order, similar to how a home cook follows a recipe. From an energy modeling perspective, the important aspects of the recipe are: how much energy and what type of energy is required at each time step. A generalized input format is proposed to capture the key information required to model the energy used throughout the process. The input format is designed so that any cooking process can be defined in the same way. The input format describes:

- The action performed
- Utility required
- Product involved in the action
- Equipment used
- Duration of the action
- Mass of the product
- Temperature change of the product
- Specific heat of the product

Each product process flow is broken down into time steps which involve a single action such as “Heat Brine Tank”. The combined time steps describe how the product is processed from start to end. These time steps are then inputted into the database following a standard input format, as illustrated in Table 1.

In conjunction with the recipe database, a 52-week schedule array is used to define a typical operating year for the facility. Any recipe that is to be run on a specific day is identified in the schedule array. For the model to accurately reflect reality, the production schedule must be developed in close coordination with plant management and operational staff.

Table 1: Example Recipe Input File

Process Step	Utility	Product	Equipment	Time	Mass	T1	T2	Cp
Fill Tank with Water	PW	Water	Brine	1	198.27	60	60	4.186
Heat Brine Tank & Mix	STM	Water	Brine	2	-	-	-	
Fill Kettle with Water	PHW	Water	Kettle	3	567.81	71.1	90.6	4.186
Add Seasoning	-	-	-	-	-	-	-	-
Add Ground Beef	STM	Grnd Beef	Kettle	4	123.78	4.4	90.6	3.339
Filler Rate	-	-	Cooker Cooler	114	Can/Min	-	-	-

The shift scheduler module uses the schedule array and recipe database to generate an operation schedule at a one minute time step. This operational schedule defines minute-by-minute batch utility requirements, temperature set-points, and product mass flow rates.

Each piece of process equipment has an individual module that is activated according to the time steps requirements defined in the shift scheduler and recipe input file. If activated, a process module reads the temperature set-points, mass flow, product-specific heat from the recipe input file. The module then calculates the utility consumption and base energy used to meet the operational requirements of a given time-step. Process equipment typically found in a food manufacturing plant includes: kettles, fryers, re-torts, fluid coolers, and other specialized equipment.

The recipe format may be adapted to many different processes. For example, Zhu et al. [2], in their energy model described in Section 1, assumed that the respiration of heat from the food would be constant. If this model incorporated the recipe format and shift scheduler as proposed in this work, they could assess how the cooling load is affected by the flow of product into and out of the warehouse [2].

Any continuously operated process equipment is modeled independently of the process modules.

2.2. Modeling On-Site Utility Generators with - Neural Networks

Any piece of equipment that generates the energy source needed by a process is referred to as a utility generator. Commonly required utilities are steam, hot water, compressed air, chilled water, and electricity. Corresponding utility generators to provide the energy sources are: boiler, water heater, air compressor, cooling tower, and electricity provider. Utility systems such as boiler and water heater may be simply modeled using the nameplate efficiency and flow rate. However, cooling towers are more complicated as the efficiency is sensitive to key parameters such as wet-bulb, approach, and range. Many models for predicting cooling towers have been developed, but they typically require iterative solutions [26] or are difficult or time-consuming to implement. As an alternative to rigorously representing the physics behind cooling tower operation, a neural network can be used to predict operation at any time step over a wide range of conditions. Neural networks have been shown to reliably predict performance. Hosoz demonstrated that NN can reliably predict performance with errors ranging from 0.89-4.64% [27]. Gao investigated NN accuracy of predicting cooling tower performance in cross-wind condition [28]. Mohanraj expanded the use of NN to model building HVAC system [29].

The user implements a neural network by (1) requesting operational data from the manufacturer (which aligns with the expected process conditions) then (2) training the network to the data-set, and finally (3) writing the function to accept weather data and cooling water inlet and outlet conditions. For the model developed here, the Levenberg-Marquardt algorithm was used for training neural networks [30].

2.3. Heat Recovery and Optimization

The model may be used for predicting annual energy costs, sizing utility equipment, or calculating annual production throughput. With respect to energy conservation, the proposed modeling technique is able to demonstrate energy flows throughout the process at each time step. The output from the model may be used to assess which streams are available for heat recovery, the temporal relationship of streams, and the magnitude of available heat.

Depending on stream availability and timing of supply and demand, a direct or indirect heat recovery system may be implemented to transfer heat between streams. Batch processing is highly irregular and often does not operate at steady state, which greatly complicates equipment sizing because it requires the consideration of many different design iterations. However, it has been shown that optimization software is capable of providing discrete solutions over the course of many time steps [25].

3. Case Study

3.1. Facility Energy Model

The modeling framework was applied to a small seasonal cannery located in Harrisville, Utah. The cannery is operated seasonally in 1-2 week periods. Thirteen primary products are processed at the cannery ranging from chicken noodle soup to green bean cans. Products are run continuously until the can quota is reached. Each product is unique in its energy requirements but the generic product flow is illustrated in Figure 2.

Raw ingredients are delivered to the cannery, cleaned, sorted and cut according to the recipe specifications. Raw ingredients are blended with water and either brined or cooked in kettles. The brine and kettle tanks require process water, hot water, and steam. Once fully processed the ingredients are canned and sterilized in a cooker-cooler before being packaged.

The cooker-cooler (retort) is continuously operated for all recipes and for the duration of each shift. Cans enter the cooker-cooler at ambient conditions and are heated, with steam, to sterilization temperature in the first zone. Once sterilized, the cans progress into the cooling side of the cooker-cooler, zone 2, where they are cooled with tower water to approximately 85°C. The heating and cooling zone model is a simplified energy balance, equation 1 and equation 2, as proposed by Simpson [31]. Through zone 1 and zone 2 the product in the can is assumed to be homogeneous and isotropic. Heat loss through the insulated cooker-cooler and warm-up time are small.

$$\dot{m}_{steam} * h_{steam,fg} = \dot{m}_{can} c_p (T_{out} - Tin) \quad (1)$$

$$\dot{m}_{tw} c_{p,tw}(T_{w,out} - T_{w,in}) = \dot{m}_{can} c_p(T_{out} - Tin) \tag{2}$$

Can flow rate is determined through the shift scheduler and the temperature set-points for each zone are held constant. Corresponding utility flow rates and cooling water temperature are calculated based on an energy balance across the cooker-cooler.

Steam for the cooker-cooler, kettles, brine tanks, process hot water generator and hot water generator is provided by a 600 HP boiler.

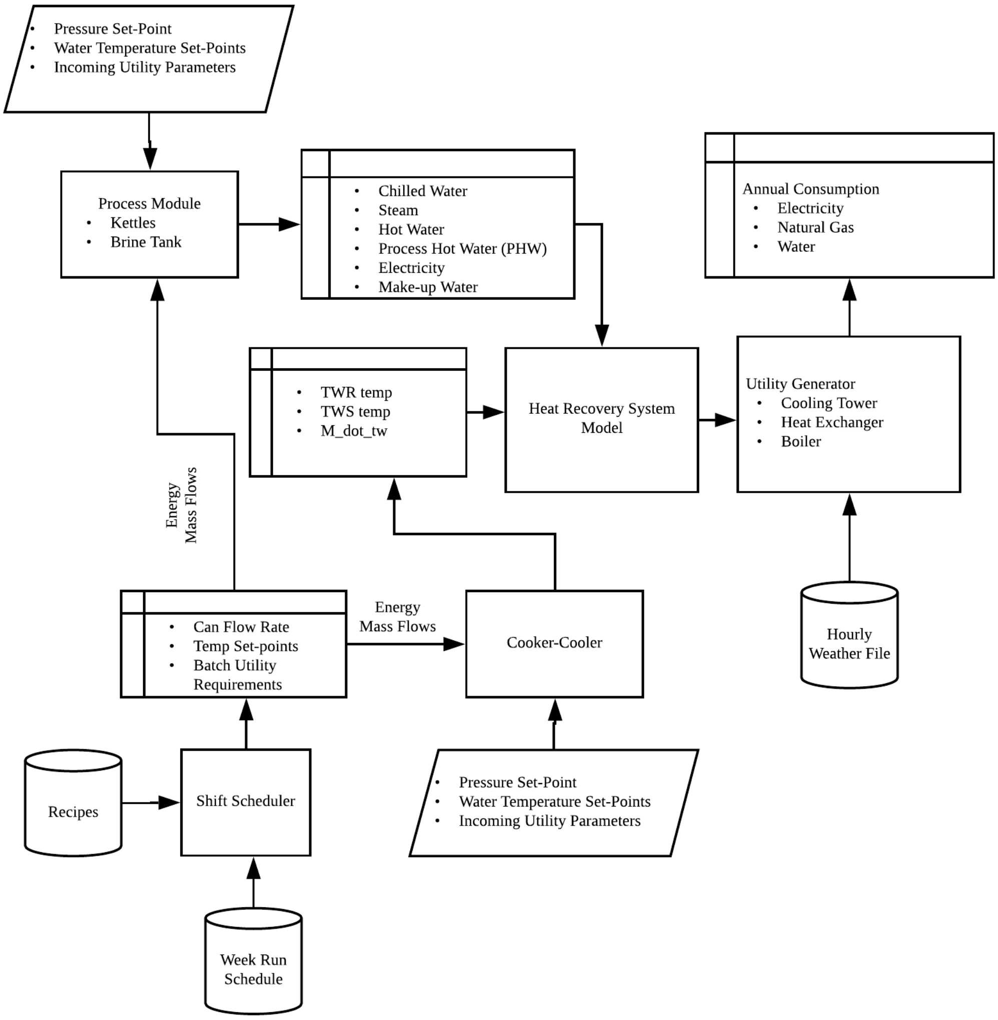


Figure 2: System Block Diagram

3.2. Cooling Tower – Neural Network

The cooker-cooler cooling section (zone 2) is cooled by cold water. The cooling water is circulated from the cooling section to a roof-mounted cooling tower. The cooling tower rejects the heat from the cooling section of the cooker-cooler to atmosphere. Accurately predicting the fan speed at each time step is difficult because ambient conditions and varying range affect the performance of the model. Several cooling tower models have been proposed; however most rely on iteration to solve. Rather than relying on an iterative solution method, a neural network (NN) toolbox was used to develop a predictive model. Fifty state points at conditions typical throughout the year were used to train the neural network. All state points were provided by the cooling tower manufacturer, BAC [32]. The NN is programmed to read the ambient wet-bulb, cooling water mass flow rate, tower water return, temperature, and range. Given the inputs, a predicted set-point for the fan's variable frequency drive is calculated. The neural network fan speed is verified against conservation of mass and conservation of energy across the cooling tower's system boundary. Equations 3-11 are simultaneously numerically solved [33].

An energy balance across the cooling tower is given by equation 3.

$$\dot{m}_{tw,f} * h_{tw,out,f} = \dot{m}_{a,out} * (h_{a,out} - h_{a,in}) + h_{tw,out} * (\dot{m}_{tw,f} - \dot{m}_{w,makeup}) \tag{3}$$

Then a mass balance across the cooling tower control volume is given by equation 4.

$$\dot{m}_{w,makeup} = \dot{m}_a * (\omega_{out} - \omega_{in}) \tag{4}$$

Leaving air humidity ratio may be solved using equation 5.

$$\omega_{out} = \frac{(2501 - 2.326 * wb_{air,out})\omega s_{out} - 1.006(db_{out} - wb_{air,out})}{2501 + 1.86 * db_{out} - 4.186 * wb_{air,out}} \tag{5}$$

Leaving air wet bulb temperature may be solved as a function of relative humidity and dry-bulb using equation 6 [34].

$$\begin{aligned} Twb_{air,out} = (&Tdb_{out} * atan0.151977 * (100 * RH_{out} + 8.313659)^{0.5} \\ &atan(Tdb_{out} + 100 * RH_{out}) - atan(100 * RH_{out} - 1.676331) \\ &0.00391838 * ((100 * RH_{out})^{3/2}) * atan(0.023101 * 100 * RH_{out}) - 4.686035) \end{aligned} \tag{6}$$

With relative humidity defined as equation 7.

$$RH_{out} = \frac{pw_{out}}{pws_{out}} \tag{7}$$

The degree of saturation for the air leaving the cooling tower is given by equation 8.

$$\omega s_{out} = \frac{0.621945 * pws_{out}}{p_{total} - pws_{out}} \tag{8}$$

The water vapor saturation pressure and the humidity ratio of the leaving air are given by equations 9 and 10 respectively.

$$pws_{out} = \exp \frac{c8}{Tdb_{out}} + c9 + c10 * Tdb_{out} + \\ c11 * Tdb_{out}^2 + c12 * Tdb_{out}^3 + c13log(Tdb_{out}) \quad (9)$$

$$pw_{out} = \frac{p_{total} * \omega_{out}}{0.621945 + \omega_{out}} \quad (10)$$

Finally, the enthalpy of the cooling tower leaving air is solved as a function of dry-bulb temperature and degree of saturation.

$$h_{air,out} = 1.006 * Tdb_{out} + \omega_{out} * (2501 + 1.86 * Tdb_{out}) \quad (11)$$

3.3. Heat Recovery Optimization

The most apparent stream eligible for heat recovery is the cooker-cooler cooling loop, which operates at a supply temperature of 29.44°C and a return temperature of up to 71°C. Recovering heat from the cooling loop reduces boiler fuel needs, fan power in the cooling tower, and cooling tower make-up water. Waste heat from the cooling loop may be utilized to pre-heat water supplying the hot water and process hot water generators which require hot water at 60°C and 71°C respectively. Whether the heat recovery method is direct or indirect depends on the availability of the cooling loop and the hot water generators. The cooling loop operates continuously and results from the model indicate that the hot water generators have a 22% availability. The low availability of the hot water generators dictates that an indirect heat recovery method will maximize performance [21].

The indirect heat recovery system consists of a hot water buffer tank coupled to the tower water loop through a heat exchanger and circulation pump. The demand side of the hot water buffer tank is installed inline with the process and hot water generator cold water feed. See figure 3 for the heat recovery system diagram.

Hot water buffer tanks may be modeled by considering the inlet and outlets as the boundary of the energy balance equation. The model, as developed by EnergyPlus [35], is defined by 12 below [36].

$$\dot{m}c_p \frac{\delta T}{\delta t} = \varepsilon_{use}\dot{m}_{use}c_p(T_{use} - T) + \varepsilon_{use}\dot{m}_{use}c_p(T_{source} - T) \quad (12)$$

Equation 12 may be rearranged and differentiated to solve for the temperature of the tank at any time step.

$$T(t) = (\frac{a}{b} + T_i)e^{bt} - \frac{a}{b} \quad (13)$$

where

$$a = \frac{1}{mc_p}(\varepsilon_{use}\dot{m}_{use}c_pT_{use} + \varepsilon_{source}\dot{m}_{source}c_pT_{source}) \quad (14)$$

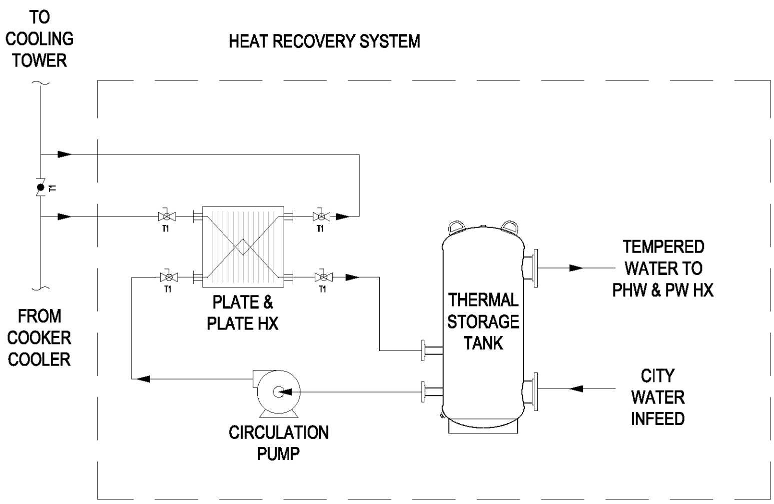


Figure 3: Heat Recovery System Diagram

$$b = \frac{1}{mc_p}(\varepsilon_{use}\dot{m}_{use}c_p + \varepsilon_{source}\dot{m}_{source}c_p) \tag{15}$$

The heat exchanger in the heat recovery system may be modeled using the NTU method as described by Janna [37]. See Appendix A for equations.

Based on equation 12, as the buffer tank volume or heat exchanger size increases, energy capture will increase. Ideally, the buffer tank and heat exchanger would be infinitely large to capture all available energy. However, as the component sizes increase, the cost of the system increases as well. To optimize the system, the component costs, cost of fuel offset (through heat recovery), and the temporal variation in hot water demand must be taken into account.

Optimization is performed by utilizing a nonlinear optimization solver. Typically nonlinear optimization tools accept matrix variables which define the lower and upper bounds of the optimization variables, a matrix of inequality/equality constraints and optimizes against a set objective function. Heat recovery introduces another level of complexity as the system is never under steady-state conditions due to process flow variation. To account for changing process conditions the heat exchanger equations described in Appendix A and equations 12 thru 15 are evaluated at each time step with the nonlinear equality constraint. All the equations are defined as a matrix array with dimensions m-by-n where m is equal to the number of equations and n is equal to the number of time steps during which the optimization variables are to be optimized, similar to Henze's approach for optimizing thermal storage systems in pharmaeutical buildings [23] and Katulic approach for optimizing a heat storage tank at a cogeneration plant [25].

For example, the equations become:

$$\dot{V}_{recirc}(i) = \frac{x(2)/\rho s x(3)}{(x(5)+1)/2} \tag{16}$$

...

$$t_2(i) = \frac{twr(i) - T_2(i)}{R(i)} + T_{tank(}i - 1) \quad (17)$$

The first equality, eqn. 18, enforces conservation of energy between the overall heat balance for the heat exchanger and the thermal change of the cold side of the heat exchanger.

$$ceq1(i) = U(i)x(3)x(4)x(5)F(i)LMTD(i) - x(2)cp_w(t_2(i) - T_{tank}(i-1) \quad (18)$$

The second equality, eqn. 19, ensures that the thermal energy change of the fluid in the tank is equal to the energy flowing into the tank minus the energy flowing out of the tank.

$$ceq2(i) = x(1)\rho_w cp_w(T_{tank}(i-1) - t_{tank}(i)) - x(2)cp_w(t_2(i) - t_{tank}(i)) \\ - \dot{m}_{hx}(i)cp_w(t_{city} - t_{tank}(i)) \quad (19)$$

where i=1:n, x(1)=Tank Volume, x(2)=Re-circulation flow rate from the thermal tank to the heat exchanger, x(3)=HX width, x(4)=HX height, and x(5)=number of plates.

Defining the equality constraints in this way allows the solver to select discrete values of each optimization variable over a set period of time.

An annual operating cost (or objective function) of the indirect heat recovery tank and heat exchanger may be defined as:

$ Profit= Annualized Cost of the exchanger + Annualized Cost of the tank - Fuel offset or

$$MinCost_{annual} = a(m_{hx} * \dot{m}_{hx} + b_{hx}) + a(m_{tank} * V_{tank} + b_{tank}) - \\ energy_{Recovered}\varepsilon_{boiler}\varepsilon_{hx}hr_{hx}Cost_{Fuel} \quad (20)$$

where a = life expectancy of the system in years. Then m and b represent a linear cost fitting [38] [39].

The solver is structured so that only the optimization variables are passed between the equality function and the objective function. In order to convey the amount of energy recovered the equality equations must be evaluated within the objective function for the entire time period under consideration [40].

4. Results

4.1. Cooling Tower Modeling

The NN was able to closely match the training data with a regression R-value of 0.993. Figure 4 shows the corresponding neural network output to (10) points from the training dataset.

The neural network in conjunction with equations 3-11 maintain a cooling tower energy balance error below 1.5% when the ambient wet-bulb is above 5°C. Below an ambient wet-bulb of 5°C the cooling tower adequately rejects heat without running the fan. The neural network performs poorly at these conditions but because fan energy is the primary concern this data may be omitted with little impact on model output.

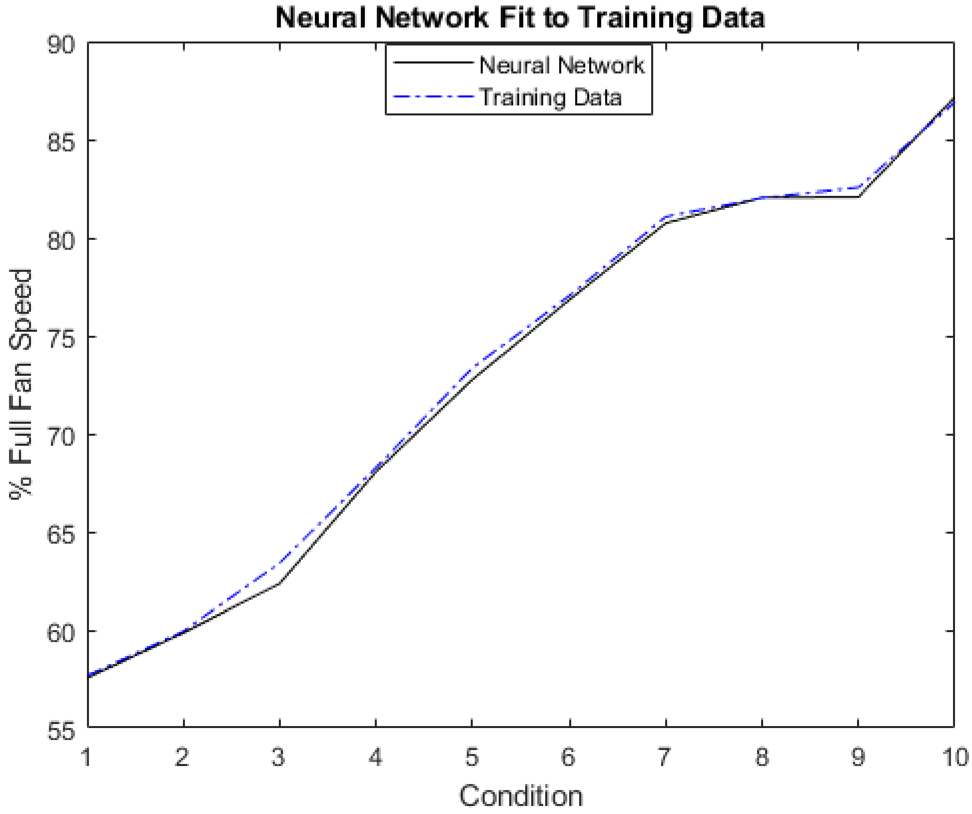


Figure 4: Neural Network Fit to Training Data

4.2. System Model

The output data from the cannery model may be used to size utility connection and size equipment. In locations with costly peak demand charges, the model may be used to determine peak consumption time and magnitude. Additionally, the model may be used to better understand how recipe impacts consumption. For example, figure 5 illustrates the hourly consumption of the plant on a summer day (August 7th) while running the Beef Stew recipe. Model output data shows that the gas consumption is cyclical and highly dependent on the recipe. Cooling tower electrical use is closely correlated to the ambient wet-bulb but the magnitude will be affected by the recipe being used. For the Beef Stew recipe, the peak hourly gas usage is approximately 375 kWh and the daily peak hourly electrical usage of the cooling tower is 5 kWh.

As mentioned previously, the basis for the case study is a seasonal cannery which operates 17 weeks per year. The model predicts that the cooling tower will require 3,597 kWhe annually and that the re-tort, kettles and brine tanks will require 1.83e6 kWh annually of gas. For a broader comparison to typical canneries, the operation schedule was increased to 52-weeks per year. For a year round, 52 week, operation schedule, electrical use increases to 1,117 kWhe annually and gas usage increases to 1.83e6 kWh annually. This correlates to 612 kJ gas/kg product and 3.6 kJ electric/kg product. The largest steam user at the facility

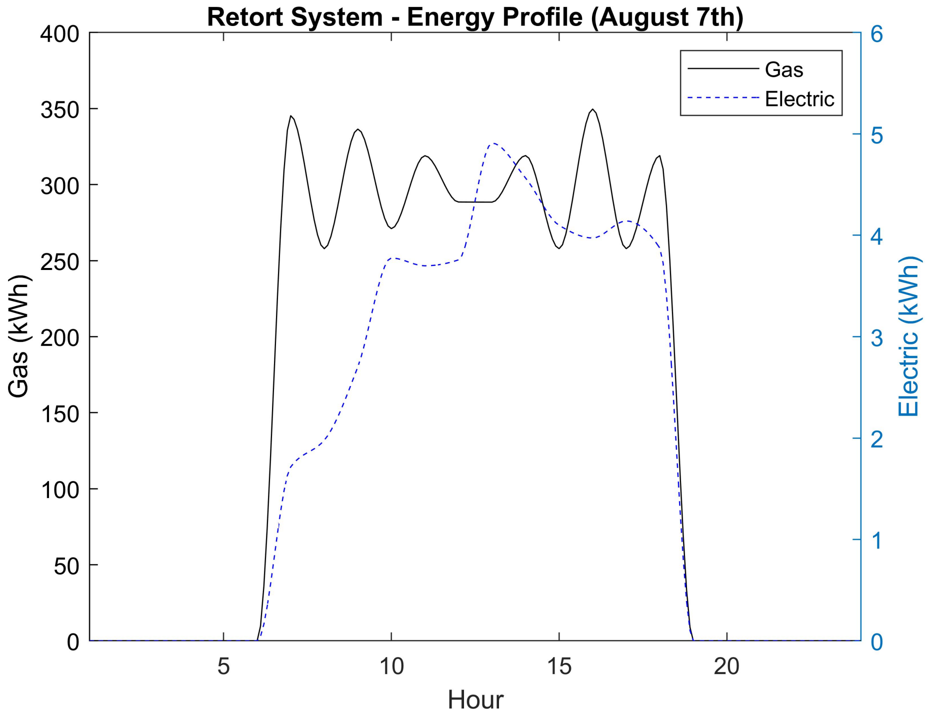


Figure 5: Hourly Energy Consumption

is the cooker-cooler which requires 447 kJ gas/kg product. Prior research indicates that a typical cooker-cooler requires 504 kJ/kg product [4, 5].

4.3. Optimization

The optimization scheme was run for each recipe individually on a daily basis. See table 2 for the resulting heat recovery system equipment sizing determined using the nonlinear optimization developed for this case study.

Table 2: Optimization Results

Scenario	Volume (m^3)	Recirc Rate (kg/m)	HX Width (m)	HX Height (m)
Green Beans - Continuous	1.16	172	0.2468	0.3600
Beef Stew - Continuous	1.36	200	0.300	0.433
Chicken Noodle - Continuous	1.34	199	0.212	0.627
Beef Chunks - Continuous	1.15	184	0.181	0.360
Turkey Chunks - Continuous	1.168	191	0.180	0.406
Average	1.238	191	0.250	0.426
Relative Standard Deviation	8%	6%	31%	24%
Global Optimization	1.257	199.69	0.382	0.369

The wide range of results implies that the optimal heat recovery system size for one recipe may not align with the optimal system for a different recipe. For example, equipment sized according to the “Green Bean” recipe may be undersized as compared to what is optimal for the Turkey Chunks recipe. To find a global optimization across different recipes the optimization function was run over a hypothetical (1)-week period for which a different recipe was run each day. Figure 6 shows the impact of using optimization values from the “Green Bean - Continuous”, “Turkey Chunks - Continuous” and “Global Optimization” values.

The optimization values from “Turkey Chunks”, “Green Bean” and “Global” reduced gas consumption by 5.7%, 6% and 7% on average across all recipes. Prior literature estimated that similar heat recovery systems, in American food plants, could reduce energy consumption by up to 6% [14][15].

Best energy savings may be gained by using the “Global Optimization” values which drops electrical and gas savings to 14.12% and 6% dropping the consumption per kg of product to 576 kJ gas/kg and 3.24 kJ electric/kg. In total, gas consumption may be reduced by 133,360 kWh and electrical consumption may be reduced by 1,923 kWh annually when using the “Global Optimization” values.

Figure 7a shows the annual electrical consumption on a weekly basis for a typical meteorological year [41]. Figure 7b shows the annual gas consumption.

Implementing the proposed heat recovery system will reduce both the peak gas and electrical loads and the normal operating loads. For example, Figure 8a and Figure 8b illustrates how the heat recovery system would reduce the energy consumption on a summer day (August 7th) while running the Beef Stew Recipe.

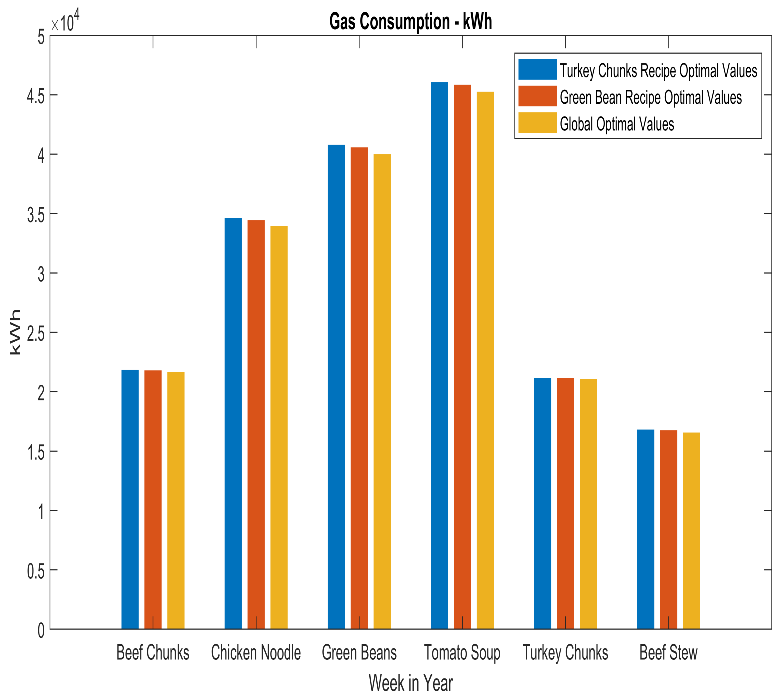
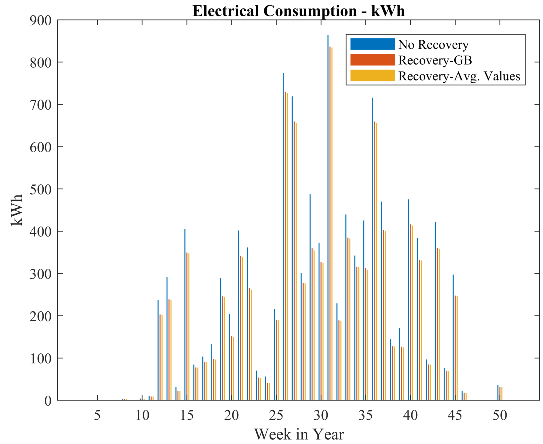
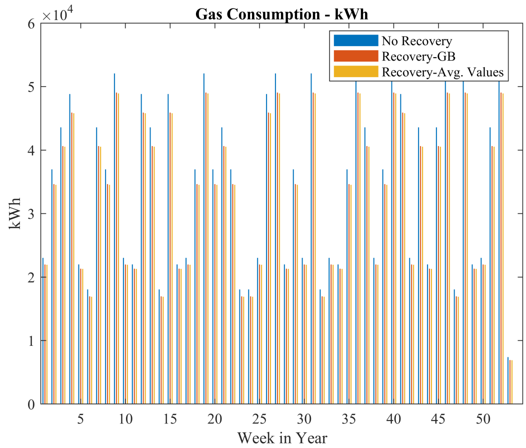


Figure 6: Impact of Optimization Approach

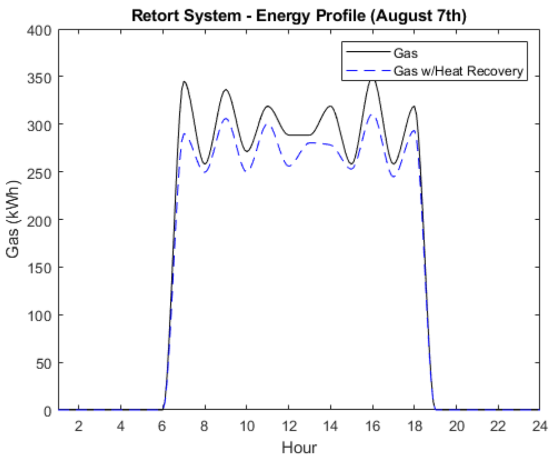


(a) Weekly Electrical Consumption

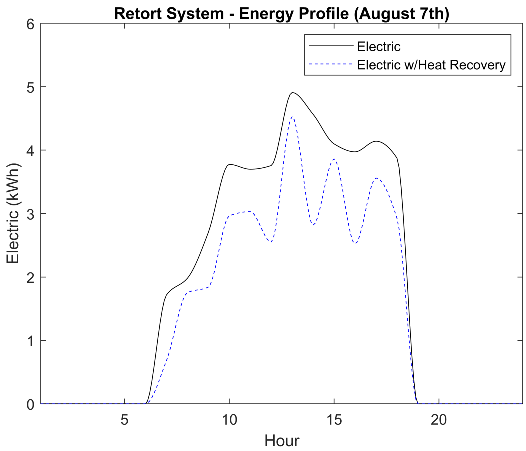


(b) Weekly Gas Consumption

Figure 7: Weekly Gas and Electrical Consumption



(a) Hourly Gas Consumption



(b) Hourly Electrical Consumption

Figure 8: Heat Recovery Impact on Hourly Energy Consumption

4.4. Model Limitations

There are inherent limitations to how this model may be applied. Sources of these limitations are: the usage of a NN for predicting the cooling tower fan speed, lack of building energy modeling for evaluating energy systems outside of the food processing equipment, and lack of consideration of thermal heat losses from individual pieces of equipment. As a result:

- When weather conditions fall outside the training data limits the NN predictions become unreliable.
  - Below an ambient air temperature of 5°C wet-bulb, the neural network predictions become unrealistic. For the purpose of the model it was assumed that below 5° wet-bulb the cooling tower would operate dry and that the fan power would thus be zero.
- The NN results may not be applicable to all processes and situations.
  - NN must be trained with data for the correct manufacturer and model number.
  - If there is a significant change to the process flow rate and temperatures the NN may also need to be re-trained with new manufacturer provided data.
  - The NN was developed with training data assuming a new cooling tower. Over time, actual cooling tower performance will deviate, especially if the tower is not properly maintained.
- Space heating and cooling loads are not considered in the current framework for optimization. Omitting the building loads artificially reduces the $\frac{kJ}{kg_{product}}$ required.
- Equipment and piping were considered well insulated and it was assumed that heat loss through convection would be small. To improve model accuracy, heat losses may be considered.

5. Discussion and Conclusions

A dynamic, modular framework was developed to estimate the energy consumption associated with operating an industrial food plant. The model is driven by food mass flow rates as defined by a set of standardized recipes format developed for this paper. Weather is also integrated to more accurately predict energy requirements. For each device such, as kettles, boilers and cooling tower, the equations are solved independently and fed back into the model. The benefit of modularity is that complex equipment may be modeled using equipment specific techniques. For example, a NN was trained using manufacturer data to simulate cooling tower performance without having to solve the physics at each time step, thereby reducing computational time.

The results obtained from the model may be presented to facility management, increasing transparency into energy costs and resource allocation, which in turn drives more informed equipment investment decisions. A final benefit is that by calculating the energy streams on a minute by minute basis it is possible to investigate the savings from heat recovery and to optimize the system across many different recipes.

The model and optimization framework was applied to a seasonal cannery assuming one shift per day. Heat recovery for the cannery is predicted to reduce gas consumption by 5.7% and cooling tower electrical consumption by 12.12%. With an estimated system cost of \$30,000 the simple payback is 15 years assuming that electricity and gas costs are 0.056\$/kWh and 7.11e-6\$/kJ respectively [42] [43]. It is important to consider that the cannery investigated is operating in a locale with very affordable energy prices and that it only has a single operating shift whereas a typical facility would have two or more shifts per day. Furthermore, the cannery is owned and operated by the Church of Latter-day Saints. All the canned food is donated to low-income houses or victims of disasters and is a non-profit facility. The facility was built to operate for over 30-years so a payback of 15-years is not unreasonable even though a typical industrial facility requires a 5-year payback [24]. If an additional shift was added the payback would be reduced to 7.5 years. Furthermore, energy consumption and payback may be reduced by utilizing the hot water for domestic usage or space heating.

A final benefit of the model framework proposed is that if the model had been implemented during the design phase it would have been possible to downsize or outright eliminate the cooling tower, which cost \$69,000, completely offsetting the capital cost of installing the heat recovery system.

While the developed model applies well to systems which are mostly gas driven it is currently lacking for systems dependent on electricity as their primary energy source. Furthermore, only water to water heat recovery was considered. For facilities that have higher grade waste heat, the model may be adapted to consider optimization for Organic Rankine cycles, as proposed by Law [44]. The model could further inform the integration of a whole building energy modeling platform, such as EnergyPlus, to develop a holistic food processing facility model including HVAC, electricity and water usage. Future work could extend food plant energy modeling to include building HVAC system through the use of NN as proposed by Mohanraj [29].

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Appendix A. Heat Exchanger equations

The heat exchanger equations are given by:

$$V_{recirc} = \frac{\dot{m}_{recirc}/\rho A}{(N_s+1)/2} \qquad V_{tw} = \frac{\dot{m}_{recirc}/\rho A}{(N_s+1)/2} \tag{A.1}$$

$$Re_{recirc} = \frac{V_{tw} * D_h}{v} \qquad Re_{tw} = \frac{V_{tw} * D_h}{v} \tag{A.2}$$

$$Nu_{tw} = \frac{hD_h}{k_f} = 0.374 {Re_{tw}}^2 Pr^{1/3} \qquad Nu_{recirc} = \frac{hD_h}{k_f} = 0.374 {Re_{recirc}}^2 Pr^{1/3} \tag{A.3}$$

$$h_{recirc} = Nu_{recirc} * k_f/D_h \qquad h_{tw} = Nu_{tw} * k_f/D_h \tag{A.4}$$

$$\frac{1}{U} = \frac{1}{h_{recirc}} + \frac{1}{h_{tw}} + \frac{1}{k_f} \tag{A.5}$$

$$N = \frac{U_o A_o N_s}{\dot{m}_{recirc}} \qquad R = \frac{\dot{m}_{recirc} C_p}{\dot{m}_{tw} C_p} \tag{A.6}$$

$$E = exp[U_o A_o N_s F(R-1)/\dot{m}_{recirc} C_p] \tag{A.7}$$

$$T_2 = \frac{t_{twr}(R-1) - R(i) * t_{tank} * (1-E)}{RE-1} \tag{A.8}$$

$$t_2 = \frac{twr - T_2}{R} + T_{tank} \tag{A.9}$$

$$LMTD = \frac{(twr - t_2) - (T_2 - T_{tank})}{ln[(t_t wr - t_2)/(T_2 - t_{Tank})} \tag{A.10}$$

$$q = U_o HX_{Width} HX_{Height} N_s F LMTD \tag{A.11}$$

$$q = \dot{m}_{recirc} C_p (T_2 - T_{tank}) \tag{A.12}$$

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