Simulating and Optimizing Mechanical Equipment for Candy Manufacturing

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ABSTRACT

Food production represents 15.7% of US energy usage. Consequently, it is important to recognize that food processors are committing to carbon neutrality. However, new energy modeling frameworks and analysis techniques are needed to reduce energy usage and emissions. One energy-intensive food process is soft-jelled candy manufacturing. Typically, it requires 5.67 kW to produce 1 kg of candy. Soft-jelled candies are traditionally made through a process called confectionery stoving. The basic steps of the stoving process are to first fill molded candy forms with a liquid slurry, insert the candy into stoves (or ovens), dry the liquid slurry to the desired consistency, and then finally cool the candy to ambient conditions. The most energy-intensive step is heating and drying the candy which can consume up to 84% of the energy at a confectionery facility. Traditionally, drying is accomplished by heating and ventilating the stoves at a high air change rate with a high percentage of outdoor air. Typical of most drying processes, the local climate of the facility strongly influences the energy required to dry the product.

This work proposes a quasi-static energy modeling framework for simulating transient process conditions in a confectionery stove. The confectionery stove considered in this work is an insulated box that is conditioned. The conditioning equipment is an air-handler with hydronic heating and cooling coils and a desiccant dehumidifier. The energy model considers the stove temperature set-point, relative humidity set-point, moisture diffusion rate of the candy, and the heat transfer rate of the candy as a function of time. Furthermore, the energy model calculates the energy required to operate the air handler and dehumidifier. Lastly, actual meteorological weather data is integrated into the framework to capture the effects of the local climate. The proposed energy model enables a Multi-objective Optimization (MOO) to search for the best set-point for ventilation rate and percentage of outdoor air to minimize energy consumption and equipment first cost. The proposed MOO algorithm is an Evolutionary Algorithm called NSGA-II which finds a set of optimal solutions that balance the trade-off between objectives commonly referred to as the Pareto Front. The optimization will be performed in climates zones Hot-Humid (2A) to Cool-Dry (5B).

These new tools will facilitate the strategic siting of new facilities in favorable climates. The hypothesis is that facilities in dry-hot climates will consume much less energy and produce fewer emissions than in cool and humid climates.

INTRODUCTION

Confectionery stoving dates to the 1700s as a way to cook soft, starch-gel candies. The tradition method occurs at ambient temperatures over a long period of time. However, as the treat is desired worldwide there is a need to produce these types of candies at the industrial scale. The industrial manufacturing of confectionery treats is very energy intensive. For example, confectionery manufacturing is the 11th energy consumer of food processing plants in Poland (Wojdalski et al., 2015). The industrial food production process has several steps. The first step is to combine all the ingredients in a boiling kettle to make a sugary gelatinous liquid. Then the mixture is deposited into trays of starch that have been pre-stamped with shapes such as fish or bears. These trays are then moved into a confectionery stove which heats and dries the candies. The stove process typically takes 12 to 24-hours (Delgado et el, 2015) to

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achieve the correct moisture content in the candies. Lastly, the candies are removed from the stove, cooled, and packaged. The stoving process is graphically displayed in Figure 1.

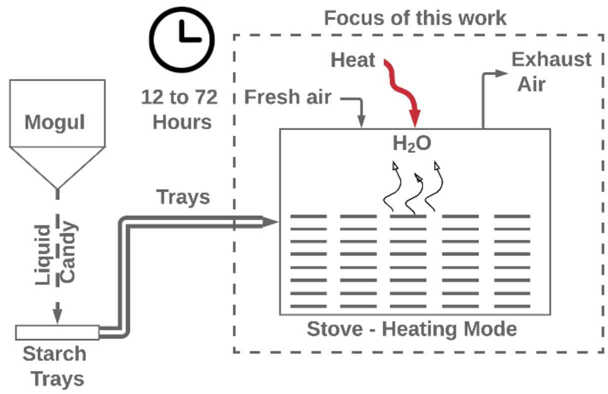

Figure 1 - Stove Process Diagram

The largest energy consumer in the soft-gelled confection cooking process is the stove. A typical stove consumes 5.617 kW/kg of product (Carbon Trust Industrial Energy Efficiency Accelerator, 2011) and accounts for up to 84% of the energy at a confectionery factory (Wojdalksi et al., 2015). Different types of stoves are available. The simplest stove heats 100% outside air to the desired set-point and blows it across the candy to dry it. While this approach is simple it provides little humidity control and requires significant energy in colder climates. A more sophisticated approach is to use an air handler with a cooling coil with re-heat to maintain a constant leaving air temperature and humidity control. The disadvantage of this system is that supercooling the air to a low humidity level and re-heating it not an efficient use of heat and electricity. Significant energy savings can be realized by using a desiccant dehumidifier instead of supercooling for humidity control. Prior studies evaluating desiccant dehumidification for pumpkin drying found that drying energy use can be reduced by up to 50% (Atuonwu et al., 2011). Another advantage of using desiccant dehumidification is that product quality is also improved (Delgado and Banon, 2015). This work focuses on the most energy efficient and highest product quality system which consists of an air handler and desiccant dehumidifier. See Figure 2 for the process flow diagram considered in this work.

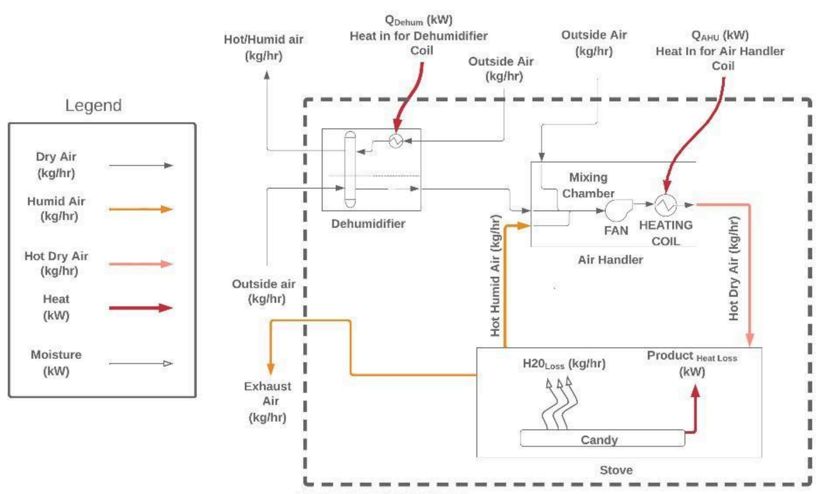

Figure 2 - Stove System Process Flow Diagram

Outside air crosses the system boundary of the stove, as is shown in Figure 2, which consequently means that local climate conditions impact the energy required to operate this stove. Furthermore, because weather changes throughout the day the stove can't be modeled under steady state conditions. Therefore, a quasi-static energy model is necessary to capture the transient effects of weather and moisture loss from the candy. Designing a highly efficient and cost-effective stove is challenging because of all the different factors discussed. One approach used in previous food manufacturing studies has been to utilize multi-objective optimization (MOO). These studies have included food distribution networks (Rong et al., 2011), beef supply chain (Soysal et al., 2014), renewable energy at groceries stores (Burek and Nutter, 2019), pineapple drying (Manonmani et al., 2017). One aspect excluded from prior works is the integration of weather data into the optimization.

This work will build on previous research by developing a quasi-static energy model framework unique to the confectionery stoving process and then utilize MOO as a tool for evaluating the tradeoffs between first cost and energy consumption in different climate zones with actual meteorological data.

METHODOLOGY

The underlying driving factor for modeling time-dependent food process systems is the recipe being cooked. To capture the effects of the recipe a database is developed that includes the thermal properties and mass of the ingredients, operation setpoints and the duration of type of each cycle. The approach is further detailed in a previous work (Legorburu and Smith, 2018). The energy model uses this data as an input to calculate the heat (supply air temperature) and moisture removal (supply air humidity setpoint) necessary to maintain the stove at the conditions defined in the recipe.

In conjunction with the recipe the different stove components are defined mathematically. The air handler heating coil is simulated via a first law energy balance. Desiccant wheels are much harder to model using solely first principles because of transient mass transfer. To reduce computational time, Becalli's "simplified model" is used to represent the dehumidification heat energy. The model requires eleven equations to predict the performance of the dehumidifier at different operating conditions. At each timestep, the eleven equations are iteratively solved to calculate the heat required on the regeneration side of the dehumidifier. Most of the moisture load is due to evaporation of the product as it dries in the stove. This work uses drying curves of confection stoves (Sudharsen et al., 2014) and a moisture diffusion function to predict the quantity of water that must be removed by the dehumidifier at each time step.

Weather is the final input to the energy model because the stove requires a continual percentage of outdoor air to maintain humidity levels. Standardized weather files make it possible to evaluate stoves in different climate zones. The energy model developed in this work uses actual meteorological year (AMY) weather files as the input source (University of Utah Department of Atmospheric Sciences, 2016).

The high-level computations flow is illustrated in Figure 3. The model reads input parameters from the weather file and recipe, determines if heating is required and calculates the heat input necessary for the dehumidifier and the air handler. This process iterates every 15-minutes over the course of one year.

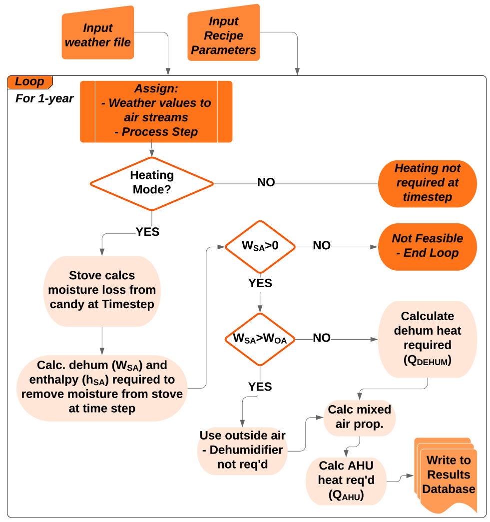

Figure 3 - Energy Model Framework

Candy drying is performed at set temperatures and humidity design points. However, as is typical for many thermal processes, control variables can be varied across a wide range to meet the pre-defined operating parameters. In the case of candy stoving the air circulation rate and the percentage of outdoor air can be varied to maintain the appropriate temperature and humidity within the stove. Selecting the best combination of air flow and outdoor air percentage from the total solution space is difficult because they are dependent on the local climate, the recipe being made and the objectives of the client. Fortunately, prior work has already shown that multi-objective optimization is an ideal tool to search large solution spaces when considering time-dependent, multi-criteria and multi-objective problems. This work applies the NSGA-II (Deb et al., 2002, Hadka, 2015) algorithm to a novel framework for finding the solution set that minimizes air handler energy, dehumidifier energy and first cost of candy stoves. NSGA-II was selected optimization algorithm because it is fast to converge, straight-forward to implement, and has been implemented in previous drying application problems (Winiczenko et al., 2018, Zeng et al., 2018). Equations 1 through equation 5 define the objective functions and constraints used in the optimization.

$$Eqn\ 1:\ Minimize:\ AHU_{Energy} = \sum_{n=15\ min}^{1\ year} \dot{m}_{MA}\left(h_{RA} - h_{SA}\right)$$

Where MA = mixed air, RA=return air, SA=supply air.

$$Eqn\ 2:\ Minimize:\ Denum_{Energy} = \sum_{n=15\ min}^{1\ year} \dot{m}_{regen}\left(h_{regen} - h_{OA}\right)$$

Where regen=Regeneration air, OA=Outdoor air

$$Eqn\ 3:\ Minimize:\ Cost = AHU_{Cost} + Dehum_{Cost}$$

Equation 4 constrains the optimization so that the supply air humidity is always positive because it is not possible to have a negative humidity ration.

$$Eqn\ 4:\ W_{SA} \geq 0$$

$$Eqn\ 5:\ AHU_{Cost} = b + m * \dot{m}_{SA}$$

$$Eqn\ 6:\ Dehum_{Cost} = b_0 + b_1 * \dot{m}_{OA} - b_2 \dot{m}_{OA}^{2}$$

Where the values of b, m, b_0, b_1, b_2 are polynomial coefficients obtained from using historical cost data (Kelbe, 2018). b=11,225, m=13,342 b_0= 17,706, b_1=39,716, b_2=2,199.

Results

This work evaluates the energy consumption of high-efficiency stoving. Then a multi-objective optimization framework facilitated the optimization of parameters to minimize energy and upfront cost. Four cities in distinct climates are considered to determine how local climate impacts the objective functions. The four cities are Las Vegas, Salt Lake City, Houston, and Omaha.

The unique framework facilitates the estimation of heat energy necessary to produce soft-gelled in different climates under varying control parameters. The estimated specific energy heat requirement to produce soft-gelled candy ranges from 1.5 to 4 kWh/$kg_{product}$. Houston is the least favorable climate for stoving because it requires significantly more energy. Increased energy consumption is attributed to higher humidity which requires increased dehumidification. Alternatively, Las Vegas is the most favorable due to low year-round humidity and high ambient temperatures. As a result of a more favorable climate in Las Vegas energy use is reduced by 11%-15%.

By performing a multi-objective optimization within each climate, the optimal air-flow rate and percentage of outdoor air can be evaluated. The trade-offs between objectives are illustrated by the Pareto fronts which includes the solution set for which parameters can't be improved without negatively impacting an objective. A portion of the Pareto Front, for Las Vegas, is summarized in Table 1. The full Pareto Front is shown in Figure 4. Selecting the final solution that best meets the goals of an organization requires some form of criteria definition. For this study, annual energy use and system first cost are considered the primary concerns. First, the solution with the lowest-energy use is defined as the base solution. Then any solution that reduces the summation of first cost and energy use percent reduction is an improvement. This type of comparison is useful because it finds solutions that significantly reduce first cost with minimal impact on energy use. For example, in Omaha the "best solution" has a 17% reduced first cost but only requires 0.2% more energy. Table 2 summarizes the resulting "best solutions" for each climate.

Table 1. Las Vegas Solution Space for Minimal Energy Use

Air Flow Kg/s	**OA%**	**AHU kWh**	**Dehum kWh**	**Total kWh**	**Total Cost USD**	**Total USD % Change**
9.1	10	657,876	140,370	798,247	186,647	N/A
9.15	10.5	660,356	138,951	799,308	187,502	+0.59%
2.64	37	664,212	126,229	800,442	100,880	-45.68%
4.77	20	666,650	134,224	800,875	129,434	-30.43%

5.15	19	674,916	135,134	802,703	135,134	-27.04%

Table 2. Analyzed Cities Climate and Objective Results

City/Climate Zone	DB (°C) Min/Max/Avg	RH Min/Max/Avg	Air Flow Kg/s	OA %	Cost USD	Energy MWh
Las Vegas / Hot dry	1 / 46/ 21.6	1.4 / 100 / 28.8	2.64	37	$100k	800
Salt Lake / Cool-dry	-16.6 / 38.2 / 12.4	21 / 100 / 63.3	3.15	31	$107k	883
Omaha/Mixed-Humid	-20.5 / 39.2 / 13.3	14.4 / 100 / 67.5	2.58	37	$99k	908
Houston / Hot-Humid	-5.6 / 36.4 / 21.2	17.3 / 100 / 78.3	2.46	40	$99k	927

The financial benefits of the high-efficiency stove are significant when compared to a traditional stove. A traditional stove does not have a dehumidifier and uses a high airflow of heated air to remove moisture from the system. The alternative optimized high-efficiency stove has a dehumidifier which lowers the amount of heating energy and volumetric airflow required. Consequently, there is a significant annual energy savings. The simple payback is summarized in Table 3 to demonstrate that the energy savings justifies the additional capital cost a high efficiency stove. Typically, a project with a payback of less than 3-years is considered financially viable.

Table 3. High-Efficiency Stove Payback Compared to Traditional Stove

City/Climate Zone	Typical Heat Intensity $kW/kg_{Product}$	Typical Heat MWH	High Efficiency Energy MWh	Gas Cost $/MW (EIA, 2022)	Energy Savings	Simple Payback
Las Vegas / Hot dry	4.9	2,457	800	$25.58	$25.58k	1.9
Salt Lake / Cool-dry	4.9	2,457	883	$25.00	$25k	2.2
Omaha/Mixed-Humid	4.9	2,457	908	$26.50	$26.5k	2.4
Houston / Hot-Humid	4.9	2,457	927	$20.20	$20.2k	3.2

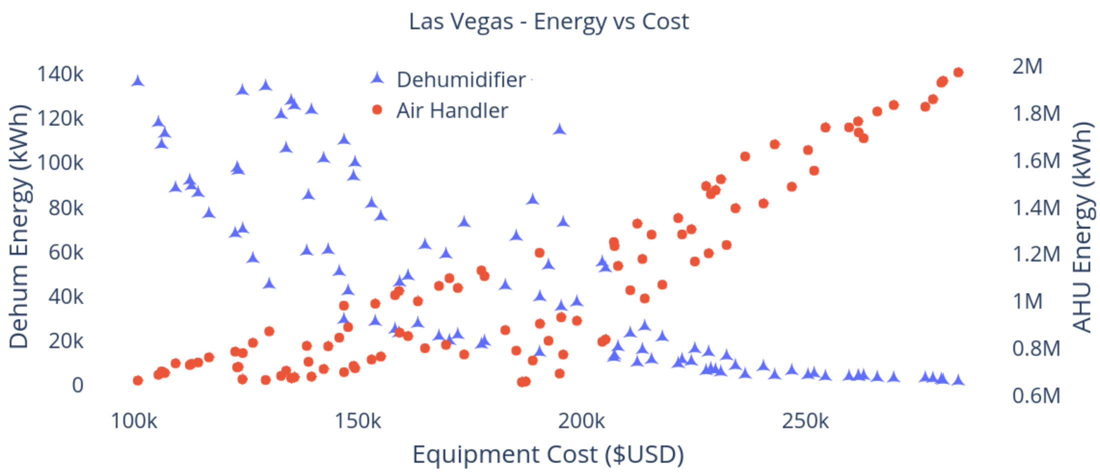

Figure 4 - Las Vegas Pareto Front

CONCLUSION

The developed energy model incorporates local weather files and product-specific recipes to estimate energy usage. Modeled conditions of a typical stove resulted in an estimated energy intensity of 4.9 kWh/kg product. Previous works showed that a conventional stove requires an energy intensity of 5.617 kWh/kg, a 12% difference from the energy model. The estimated heating energy use for a stoving system including dehumidification was significantly reduced to 1.5 to 4 kWh/kg product.

Finally, a multi-objective evolutionary algorithm was used to find the optimal stoving parameters for each city, which is a range of solutions or Pareto Front. This study proposed a Pareto Front search procedure to find the solution which has the highest percent reduction for initial cost and energy usage when compared to the most energy-efficient solution. This procedure found that initial costs can be reduced by 12-45% while only increasing energy usage by 1%. The solution optimized for initial costs saves around $30,000 - $40,000 USD annually compared to a traditional stove. This is a simple payback of 2 to 2.5 years.

In summary, this work presents a new quasi-static energy model of a confectionery stove. The framework integrates actual meteorological data to account for fluctuating ambient conditions. A multi-objective evolutionary algorithm is used to optimize control parameters. The energy model is an improvement on current confectionery stove research because the prior work didn't include ambient weather conditions and assumed that the performance of the mechanical equipment was constant. By adding weather conditions and variable mechanical equipment performance, it is now possible to forecast energy consumption of a drying stove in specific climates under varying process control parameter set points. Additionally, introducing weather data is an improvement on prior MOO work for general drying process. The research shows the benefit of strategically siting confectionery stoves by applying analysis techniques developed for the specific siting of windmills, CHP systems, and buildings. Finally, the work demonstrates that a high-efficiency stove can produce candy at a much lower energy intensity per kilogram of candy.

NOMENCLATURE

AHU	=	Air Handling Unit
Ceq	=	Nonlinear Constrain Equation

DB	=	Dry Bulb
Dehum	=	Dehumidifier
h	=	Enthalpy (kJ/kg)
humration	=	Humidity (g/kg)
m	=	mass flow (kg/s)
P	=	Pressure (kPa)
Pws	=	Saturation Water Vapor Pressure (kPa)
RH	=	Relative Humidity (as a percentage)
T	=	Temperature (°C)
Twb	=	Wet-bulb temperature (°C)
V	=	Volume (m^3)
Ws	=	Moist air saturation (kgw/kgda)

Subscripts

Air	=	Air
act	=	Actual
amb	=	Ambient
da	=	*Dry Air*
OA	=	*Outside Air*
Regen	=	*Regeneration stream of dehumidifier*
RA	=	*Return Air*
SA	=	*Supply Air*
sat	=	*Saturation conditions*
w	=	*Water*
wb	=	*Wet-bulb*

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