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Energy modeling with meteorological data and multiobjective optimization of a confectionery stove

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ABSTRACT

Confectionery stoving is the process used to produce soft-jelled candies. The stoving process has many steps, but the most energy-intensive step is heating and drying the candies, which can consume up to 84% of the energy at a factory. Drying is achieved by heating and ventilating the candy stove with large volumes of outside air, so the impact of the local climate on confectionery facilities can be significant. However, there is a lack of literature investigating local climate impact on the stoving process. This work demonstrates how Multiobjective Optimization (MOO) can be used to find a balanced solution between first cost and energy usage. Furthermore, the work investigates local climate impact to study whether strategic facility siting in a specific climate zone can significantly reduce energy needs and installation costs. The paper proposes a generic energy model that uses actual meteorological data and a product-driven recipe for calculating the energy requirement of a confectionery stove. Four distinct climate zones were analyzed, and it was found that operating a stove in a dry, hot climate, such as Las Vegas, requires 15% less energy than a hot-humid climate, such as Houston. The energy model incorporates a Multiobjective Evolutionary Algorithm (MOEA) procedure to minimize energy usage and initial cost. The algorithm varies the airflow rate and percentage of outdoor air used in the stove. A Pareto Front search procedure is defined, which compares all solutions against a "base case" solution. The base case can be the minimum of any objective, but for this work, it is the lowest energy consuming solution. The search procedure found a preferred solution where a small increase in energy consumption, 0.2%, reduces first cost by 12%–45%. The methods outlined in this paper apply to any energy-consuming manufacturing process that is influenced by climate or any such process that has a broad set of functional operating parameters.

1. Introduction

Confectionery stoving has been used since the early 1700s to produce soft, starch-gel based candies. Traditionally, candy drying occurs over a long period of time at ambient conditions. As interest for these treats has expanded worldwide, the manufacturing process has been modernized to keep up with demand. Contemporary confectioners use a myriad of production techniques ranging from traditional methods to highly automated robotic production lines. Confectioneries are energy-intensive facilities; they have been studied to identify the energy requirements and how to reduce energy consumption. A study by Wojdalski found that confectioneries ranked 11th for total energy consumption in food processing plants in Poland (Wojdalski et al., 2015).

The industrial production process of soft-gelled candy consists of multiple steps. The first process occurs in a machine referred to as the Mogul. Assortments of sugars are boiled then mixed with a gelling agent. Then the mixture is deposited into a bed of starch, which has been pre-stamped with the desired shapes. The starch bed acts as the forming mold to produce candies in a variety of shapes such as fish, fruits, animals, and people. The starch beds with the deposited candy slurry are placed within a machine commonly referred to as a candy stove. A candy stove is similar to an insulated box. The stove's function is to store the candy at an elevated temperature (40 to 60 °C) or for a prolonged period so that the majority of the moisture in the candy evaporates until the candies reach the desired moisture content (Edwards, 2018). Gelatin-based candies require 12 to 24 h to dry (Delgado and Bañón, 2015), while different sugars such as pectin can take up to 72 h to dry depending on the process (Ziegler et al., 2003). See Fig. 1 for the process up to the drying stage. After drying is complete, the stove cools the candy for post-processing and packaging

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Nomenclature

AHU	Air Handling Unit
Ceq	Nonlinear Constraint Equation
c_p	Specific heat at constant pressure (per unit mass)
DB	Dry bulb (°C)
$DEHUM$	Dehumidifier
h	Enthalpy (kJ/kg)
$humratio$	Humidity (g/kg)
$\dot{m}$	Mass flow rate (kg/s)
P	Pressure (kPa)
pws	Saturation Water Vapor Pressure (kPa)
q	Heat Transfer Rate (kW)
RH	Relative humidity (as a percentage)
T	Temperature (dry bulb, or bulk conditions, °C)
Twb	Wet bulb temperature (°C)
V	Volume (m^3)
$\dot{V}$	Volumetric flow rate
Ws	Moist air saturation (kg_w/kg_{da})
ϕ	Relative humidity (as a fraction)
ω	Humidity ratio (kg_w/kg_{da})

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

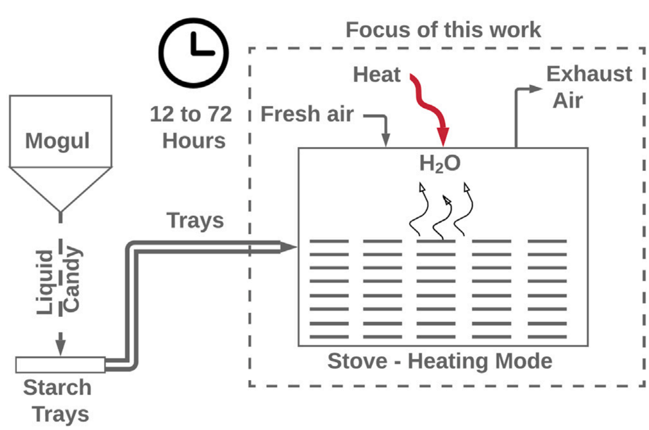

Fig. 1. Mogul to heating.

which is depicted in Fig. 2. Once the oven cooling cycle is complete, the stove is emptied, filled with candy, and then the process repeats.

The largest energy user when producing soft-gel confections is the stove oven. A typical stove consumes 5.617 kW/kg of product (Carbon Trust Industrial Energy Efficiency Accelerator, 2011) and can consume up to 84% of the energy at a factory (Wojdalski et al., 2015). There is a wide range of stoving techniques. The simplest is to heat ambient air and blow it across the candy for up to 72 hours. Using ambient air is a very cost-effective approach, but it does not provide any humidity control, which can lead to product wastage. A common, but more expensive method is to install air handlers with mechanical supercooling and re-heating to maintain a constant leaving temperature and humidity setpoint. Dehumidification with supercooling is a reliable and straightforward control technique, but there is a substantial energy disadvantage. A widely studied and popular approach for drying food products is to use an air handler and desiccant dehumidifier. The dehumidifier removes the moisture from the air, and then the air handler heats the air. A desiccant dehumidifier uses less energy than supercooling because the air does not have to be cooled. The fundamental principle is that the desiccant is a material that attracts and holds moisture. The moisture attracting property of the desiccant allows moisture to be removed from the supply air stream and is rejected to an exhaust air stream. Atuonwu shows one example of the beneficial use of desiccant dehumidifiers. Atuonwo found that using a desiccant dehumidifier could reduce the specific energy of drying pumpkin by up to 50% (Atuonwu et al., 2011). In addition to lowering the drying energy, dehumidification has also been shown to improve product quality (Delgado and Bañón, 2015). This work will focus on a high-efficiency stove system that uses an air handler coupled with a desiccant dehumidifier because prior work has shown that this can reduce energy usage and improve product quality. See Fig. 3 for the schematic of the proposed stove system.

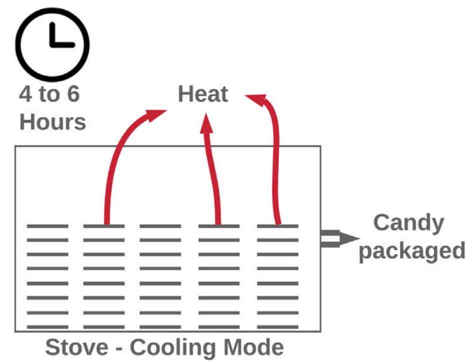

Fig. 2. Cooling to packaging.

Sizing and selecting the mechanical equipment to condition candy stoves can be challenging because ambient conditions and the types of product have a substantial effect on the thermal loads. Determining the control parameters of the stove has a direct impact on equipment cost, energy requirement, and product quality. The identification and optimization of control variables in the food processing industry have been popular topics for study. For example, Miranda developed a model of a tomato concentrate evaporator to find what control variables were important (Miranda and Simpson, 2005). The complex nature of the stove system and the desire to minimize equipment cost while minimizing energy requirements suggest that multiobjective optimization (MOO) can be very beneficial in designing these types of systems. Applying MOO to candy stoves is a unique application, but recent work indicates that MOO is a practical approach for designing mechanical systems in the food and beverage industry.

MOO has been applied to improve food distribution networks. For example, Rong et al. (2011) used MOO to model and design food distribution networks while optimizing for food quality and criteria. Soysal et al. (2014) used MOO to investigate ways to minimize logistics cost and greenhouse gases for the beef supply chain. Bortolini used a linear programming approach to optimize the cost emissions and delivery time of fresh food distribution (Bortolini et al., 2016). Burek and Nutter (2019) used MOO to find optimized solutions for purchasing renewable energy at multi-facility grocery distribution networks.

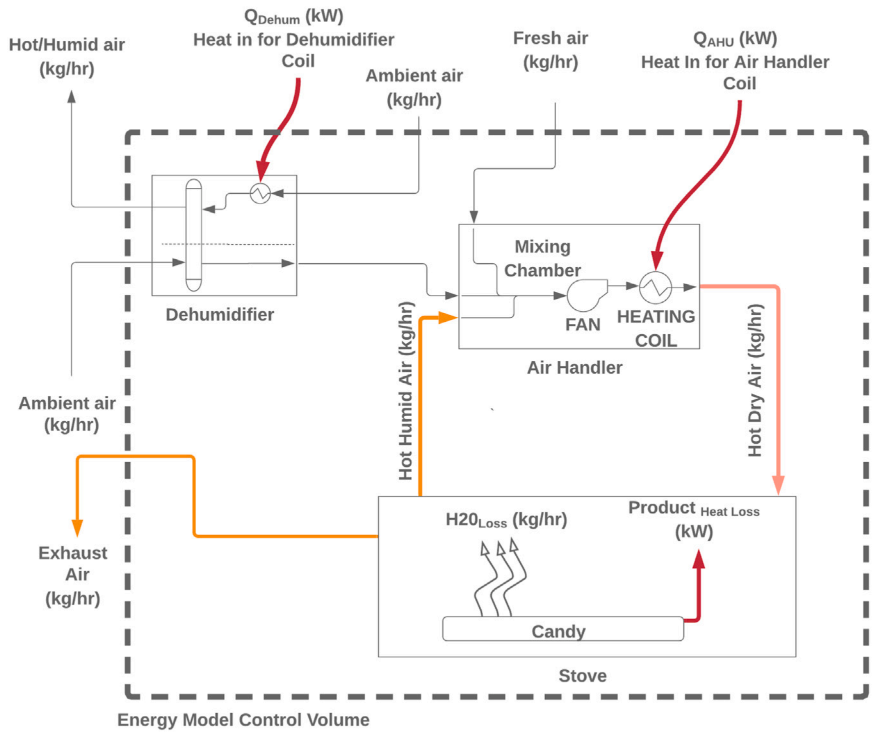

Fig. 3. Stove system PID.

MOO has also been applied to the design of thermal systems. For example, Mokhtar et al. (2017) uses a multiobjective evolutionary algorithm (MOEA) to find the solution space for a waste heat recovery system typically found in food and beverage processing facilities.

This work specifically addresses the optimization of the confectionery drying process. This is a new application of MOO optimization, but there has been work that utilized MOO for similar drying processes. For example, Szparaga used MOO to minimize the cost, dehydration period, and storage time for dehydrated plums (Szparaga et al., 2019). Szparaga found a distinct optimal solution when considering all objectives and then a different solution when maximizing the quality of the product. An interesting paper by Manonmani used MOO to develop a control scheme to reduce cost and maximize quality when drying pineapple (Manonmani et al., 2017). A recent study by Reinheimer focused on optimizing the operating conditions for hard candy drying. While Reinheimer did not use multiobjective optimization, the work developed a mathematical model of the process and then minimized annual operating costs (Reinheimer et al., 2013). Reinheimer's model fixed the performance of mechanical equipment such as the cooling tower and blowers. Furthermore, neither Reinheimer et al. (2013), Szparaga et al. (2019), or Manonmani et al. (2017) accounted for fluctuating weather conditions in their optimizations. This work further improves the state of the art by integrating actual meteorological data into the optimization process and dynamically representing the mechanical equipment. By using real weather data, the energy model accounts for the influence of the local climate.

Local climate can have a profound impact on any mechanical system. Researchers have widely studied the behavior and performance of mechanical systems in the commercial and institutional industries. Mago et al. investigated the emission reduction potential of CHP systems in different climates (Mago et al., 2011). Another example illustrating the impact climate has on a thermal system was performed by Dirks et al. (2015). This study investigated the impact of climate change on the energy consumption of commercial and residential buildings across different regions of the U.S. with unique local climates.

The impact of local climate on wind turbines has also been studied. Mirghaed et al. performed site-specific optimization of wind turbines in three different regions in Iran. Mighaed et al. found that there were unique optimal configurations for each site (Mirghaed and Roshandel, 2013). Jung et al. developed an improved methodology for siting windmills in Germany, which considered the local wind zone, geographical restrictions, siting scenarios, and life cycle cost (Jung et al., 2018).

Given that food processing is a medium to high energy-intensive industry, there is a notable lack of research investigating the impact that climate can have on facility energy use. Common factors that are important to consider are taxation, exchange rate, transportation, demand, and labor pool (Lee and Wilhelm, 2010). Considering the impact of climate on the energy intensity of food production can result in significant energy savings. In particular, drying processes such as confectionery candy stoves are susceptible to ambient humidity and temperatures. The U.S. alone has seventeen distinct climate zones ranging from Very Hot-Humid to Subarctic (Briggs et al., 2003).

The key contributions of this work are to:

- Create a recipe-driven energy model of a confectionery stove
- Optimize system parameters to minimize equipment cost and energy consumption
- Investigate local climate impact on confectionery stove operation and energy consumption
- Compare traditional stoves to high-efficiency stoves

Prior work identified the moisture diffusion rate (Delgado and Bañón, 2015), drying time (Sudharsan et al., 2004), and developed a framework for assessing the energy consumption of an operating confectionery (Miah et al., 2015). This work builds upon prior work and advances state of the art by introducing several novel components.

The first novel aspect presented here is the development of a quasi-static energy modeling framework that makes it possible to forecast the energy consumption of a drying stove under different operating conditions. The framework gives operations management the tools to simulate and optimize the stoving process before implementing changes to production.

The second novel aspect is the integration of actual meteorological data with the energy modeling framework. By including weather data, it is possible to investigate the impact of local climate on the energy required for any drying process. For an existing food production facility, the advantage of incorporating weather data into the model is that it gives additional input to energy use predictions for planning their food production-distribution operations. For potential food production facilities, the producers can incorporate weather data to improve the energy efficiency of their specific process by considering the favorability of climates toward energy savings in their decisions about strategically siting their facilities. This work introduces a novel specific siting approach for the confectionery industry and provides case studies in four distinct climatic environments.

Lastly, the framework incorporates Multiobjective Evolutionary Algorithms (MOEA) to optimize control parameters to minimize equipment cost and energy usage. Applying a MOEA to the stoving process in conjunction with quasi-static energy model and actual meteorological data is a novel method to improve the sustainability of stoving design, select the optimal location to build drying facilities, and to simulate drying processes.

2. Methodology

2.1. Energy model

The model consists of databases for recipes and weather data, an energy model for a confectionery stove, an energy model for the air treatment system, and a psychometric calculator. See the system block diagram, Fig. 5, for the organization of the databases, stove energy model (Stove), air treatment energy models (AHU and Dehum) and the psychometric calculator (Psych) (Legorburu, 2017).

Stoves may be used to produce soft jellied candies made of pectin, gelatin, sugar, and starch. Each ingredient has different characteristics such as density, specific heat and moisture diffusivity. Cooking high-quality treats requires different temperatures and durations for various formulations. To account for the ranges of conditions, a generic recipe database may be used to break the stoving recipe into a standardized input format. The recipe database includes the thermal properties and mass of the ingredients, operation setpoints, and the duration and type of each cycle. The recipe follows the format developed for modeling a cannery plant in previous work (Legorburu and Smith, 2018).

A commonality of all stove confectioneries is the stove itself. At its purest manifestation, it is a household oven. Industrial facilities commonly use air handlers, dehumidifiers, and robotic loaders. For all stoves, the objective is the same: to remove the moisture from the candy gel until it solidifies into a mechanically soft but durable texture. The stove function accepts the recipe as an input and calculates the heat (supply air temperature) and moisture removal (supply air humidity setpoint) to maintain the stove at the conditions defined in the recipe accounting for the mass and properties of the ingredients. The stove function accounts for sensible heat loss through the boundaries of the stove and moisture load from the product itself.

Moisture load from the ingredients is determined using drying curves developed by Sudharsan et al. (2004). A moisture diffusion function reads the oven cycle time, and by using the drying curves, it predicts the resulting moisture load in the stove.

Supply air setpoints, as determined by the stove function, must be maintained by treating outside air and recirculated air from the stove. A common approach for air treatment is to use an air handler with a heating and cooling coil. Sometimes, stoves require an air handler and a dehumidifier. Energy requirements for air treatment are calculated in 15-minute intervals by implementing an energy balance across the air handler coils to maintain the leaving air setpoint. Removing moisture evaporated from the product is accomplished by exhausting air from the stove, which is replenished by outside air. Consequently, the local climate can have a significant impact on energy requirements.

In certain climates, and for producers interested in reducing energy consumption, dehumidifiers are necessary to maintain the stove

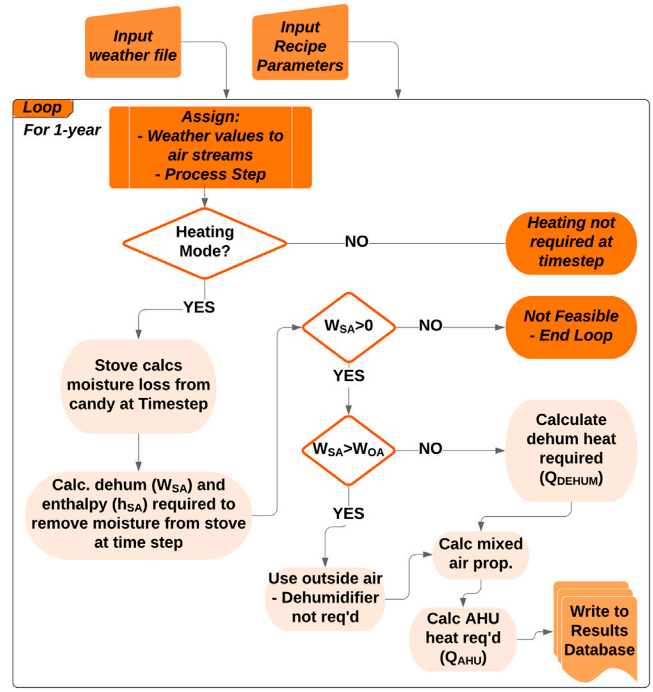

Fig. 4. Energy model flow chart diagram.

humidity setpoints. A common dehumidifier is the desiccant wheel system, which uses a rotating wheel to transfer humidity from a process air stream to a regeneration air stream. Desiccant wheel dehumidifiers are simple to operate; however, modeling them can be complex because mass transfer occurs within the desiccant wheel. Material properties and dynamic conditions govern how much mass transfer occurs. Generally, desiccant models are either mathematical models requiring computationally expensive techniques such as finite volume iterations or simplified empirically developed models. Some empirical models are reasonably accurate when predicting the performance of the desiccant wheel (Ge et al., 2008).

Beccali developed a psychometric model for estimating the performance of rotary wheel desiccant dehumidifiers. Beccali's model uses correlations for temperature, enthalpy, and relative humidity (Beccali et al., 2003). Beccali refers to this model as the "simplified model" because it only requires eleven equations to predict the performance of the dehumidifier. The model is straight-forward to implement but requires iteration to solve for the dehumidifier outlet temperature, $T_{dehum_{out}}$. Beccali's method shows reasonable accuracy for silica gel and lithium chloride wheels, with R^2 ranging from 0.8772 to 0.9948. The "'simplified model" is chosen to model the desiccant wheel because it may be implemented at low computational cost.

The high-level model flow, as illustrated in Fig. 4, is that the stove function reads the recipe and iterates through the drying cycle. Each iterative steps is a 15-minute time step. The air handler setpoints for supply air temperature and humidity are calculated at each step to maintain oven conditions defined in the recipe accounting for humidity gain (candy moisture diffusion) and sensible heat loss through the oven walls. Weather data from each timestep in an input to the air handler and dehumidifier functions. The weather data implemented in the model is actual meteorological data for the year 2017 from MesoWest (University of Utah Department of Atmospheric Sciences, 2016). Using the weather data, each function calculates and outputs the required heat to maintain the leaving air temperature and humidity setpoints.

At each time step, the regeneration heat required for dehumidification and the air handler heat necessary to maintain setpoint is

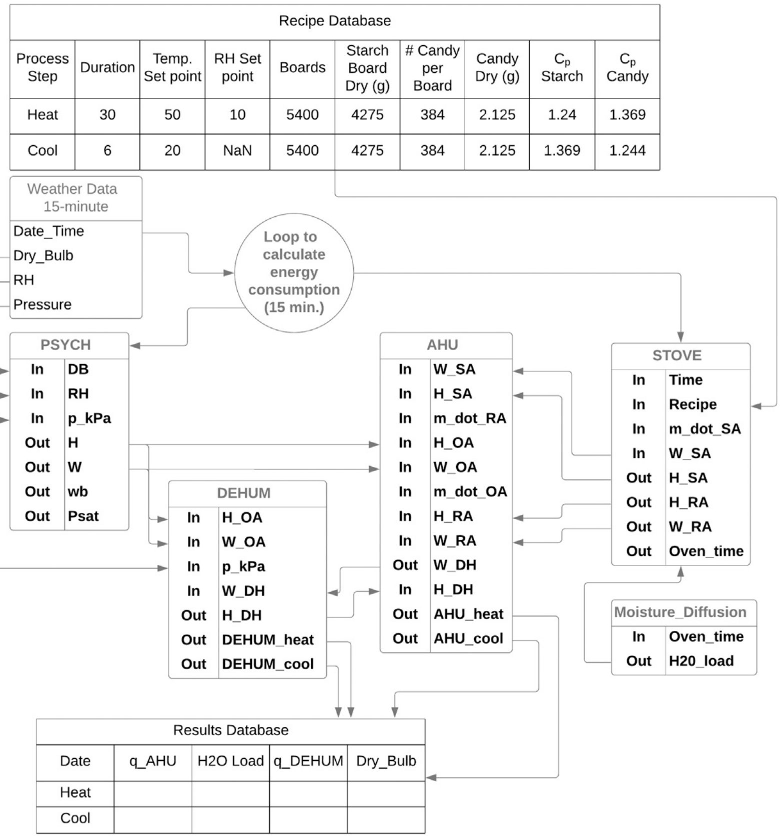

Fig. 5. Energy model system block diagram.

calculated and stored in an array. See the system block diagram in Fig. 5 for further detail.

2.2. Local climate impact

There is a global demand for soft jelled candies. To meet global demand, companies have built confectionery factories all around the world. Undoubtedly, ambient conditions affect the energy requirement of a candy stove. It is crucial to consider the local climate when finding the most advantageous location to build a candy factory.

The energy model developed for this work is designed to accept a standardized actual meteorological year (AMY) weather file as an input (University of Utah Department of Atmospheric Sciences, 2016). The energy model iterates throughout the time period and reads the weather data. Weather data is synchronized with the recipe to estimate energy consumption at each time step. The AMY files are accessible at worldwide weather stations and are downloadable from services such as MesoWest (University of Utah Department of Atmospheric Sciences, 2016). Typically, the weather stations track dry-bulb temperature, relative humidity, and atmospheric pressure. These properties are sufficient to define the state of moist air and may be used in conjunction with ASHRAE Fundamentals equations (ASHRAE, 2017) to calculate the rest of the air properties such as enthalpy, humidity, and dew-point. Each weather station may collect data at different intervals. The energy model of this works uses weather data that was collected every 15 minutes.

This approach generalizes the model so that it can evaluate the energy requirements in any climate. This work evaluates the stoving process in the following US climates: cool-dry (Salt Lake City, Utah), mixed-humid (Omaha, Nebraska), hot-humid (Houston, Texas), and hot-dry (Las Vegas, Nevada). All of the weather files used are from the year 2017. Weather data from 2017 was selected because there was a full year of consistent meteorological measurements available in all four cities which was relatively characteristic of 21st century weather in the four cities evaluated. Although there are deviations within each city when the optimization algorithm is run using a different weather year, the Pareto front of optimal solutions and the proposed solutions within each city remain similar from year to year, while the variation in the proposed solutions between climate zones is significant regardless of the weather year selected.

2.3. Multiobjective optimization

A multiobjective evolutionary algorithm is used to select the optimal solution sets for minimizing energy use cost-effectively. A non-sorted genetic algorithm (NSGA-II) (Deb et al., 2002) was chosen as the optimization algorithm because it is fast to converge and was shown to be useful for drying processes in previous works. Winiczenko et al. used NSGA-II and an artificial neural network to optimize apple drying parameters (Winiczenko et al., 2018). Zeng et al. used NSGA-II and particle swarm to optimize the drying schedule routine at a paper mill (Zeng et al., 2018). The Platypus Python library was used to implement NSGA-II (Hadka, 2015).

The underlying principle of NSGA-II is that the algorithm starts with a random population of decision variables. The decision variable values that led to a better solution become parent set for the next generation. The process repeats until any change will negatively impact one of the objectives (Konak et al., 2006). The Platypus Python library provides default parameters for NSGA-II depending on the problem type. To evaluate the performance of the default setting each parameter was changed to try to improve the Pareto solution set or reduce execution time. After several trials, we empirically set the parameters to:

- Population size = 100
- Operators

- Simulated Binary Crossover Probability = 0.95
- Simulated Binary Crossover Distribution Index = 20
- Polynomial Mutation Probability = 0.9
- Simulated Binary Crossover Distribution Index = 20

• Stop condition = 800 function evaluation
• Number of generations = 8

These parameters resulted in an execution time of 30–45 min. Evolutionary algorithms, such as NSGA-II, are stochastic in nature. To test the variance of the Pareto front, the output from the experiment detailed above was assessed. While varying the optimization parameters during five different simulations, the resulting Pareto fronts are very similar. See Fig. 6 for an overlay of five different evaluations of the Las Vegas optimization.

Implementing NSGA-II requires that the objectives are mathematically defined in terms of the decision variables so that changing the value of the decision variables impacts the objectives. Air handler energy use, dehumidifier energy use, and equipment cost are the three objectives considered; see Eqs. (1) thru (3). These objective functions enable the evaluation of how operational changes and climate will influence the first cost and energy consumption. Energy consumption is a crucial objective because it drives operating costs and emissions. Energy use for the air handler and dehumidifier is calculated at each 15-minute time step and summed throughout one year. Energy requirements are calculated by performing an energy balance across the component airside streams. The equipment cost includes equipment installation and purchase costs. The equipment cost includes installation and purchase costs. These costs are related to airflows by interpolating between discrete equipment sizes as provided in RS Means construction cost information database. (Kelble, 2018). A linear fit to tabulated data, see Eq. (5), is used to estimate the air handler installation and purchase cost. A polynomial fit to tabulated data (see Eq. (6)) calculates the dehumidifier installation and purchase cost.

The first objective function minimizes the energy required by the air handler.

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

Where MA = mixed air, RA = Return Air, and SA = Supply Air

The second objective function minimizes the energy required by the dehumidifier.

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

Where regen = Regeneration air, OA = Outdoor Air

The third objective function minimizes the equipment and installation cost for the air handler and the dehumidifier.

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

The system is constrained by Eq. (4), which requires for the supply air humidity ratio setpoint to be positive.

$$W_{SA} \geq 0 \tag{4}$$

Where W = Humidity Ratio and SA = Supply Air

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

The Air Handler cost is an approximation to cost data provided in RS means (Kelble, 2018), and b and m are the linear coefficients where b=11,225 and m=13,342.

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

The Dehumidifier cost is an approximation to cost data provided in RS means (Kelble, 2018) and b_0, b_1 and b_2 are the second order polynomial coefficients where $b_0 = 17,706$, $b_1 = 39,716$, $b_3 = 2,199$.

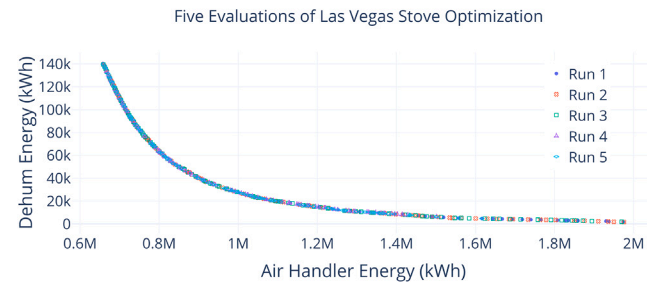

Fig. 6. Five evaluations of Las Vegas stove optimization.

The decision variables are air mass flow rate and percentage of outside air. The air mass flow rate is allowed to vary between 2 kg/s and 10 kg/s. The optimization algorithm bounds the percentage of outside air between 8% and 40%. The bounds were found through experimentation to improve execution time without artificially constricting the solution space. Initially, the optimization was run with minimal bounding and a high number of function evaluations. After finding the unbounded Pareto front, it is possible to narrow the bounding criteria to improve execution time. Outside air is directly related to the dehumidifier flow rate. All outside air is dehumidified in the desiccant wheel and mixed with the supply air to replenish the air exhausted from the stove. Furthermore, dehumidifier air is assumed to be equal to regeneration air. As evident in the objective equations, Eqs. (1) thru (3), the decision variables directly affect the three objectives.

2.4. Computer model implementation

Python version 3.7.3 was used to implement the energy model. Lucid Chart and Plotly were used to build the diagrams and plots. The energy model code and supplemental 3-D Pareto Fronts are publicly available at https://github.com/SSESLab/Confectionery-Stoving-Energy-Model.

3. Results

3.1. Energy model

The energy model provides a quasi-static simulation of a high-efficiency candy stove. The stove is essentially an insulated room that stores the product throughout the drying process. On the top of the stove, one or more steam air handlers circulate and heat the air in the stove. When the humidity ratio of the outside air exceeds the supply air setpoint, the dehumidifier will turn-on.

This study included actual meteorological data from the Mesowest database (University of Utah Department of Atmospheric Sciences, 2016). The data is from 2017 for four different US cities and is assessed in 15-minute intervals. Psychometric equations and energy balances from ASHRAE were used to model the air handler and to define the air states at various locations in the system (ASHRAE, 2017). Appendix B includes the equations used. The dehumidifier was modeled using simplified empirical equations (Beccali et al., 2003). The specific energy heat requirement (kWh/kg product) ranged from 1.5 to 4 kWh/kg product depending on the air mass flow rate through the air handler and the percentage of outdoor air used. Carbon Trust found that typical stoves without dehumidifiers require much higher heat input, up to 5.6 kWh of gas per kg of product (Carbon Trust Industrial Energy Efficiency Accelerator, 2011). The Carbon Trust report did not specify the steam generator efficiency attributed to the specific energy demand. To evaluate the direct heat requirement, it is assumed that the facilities studied by Carbon Trust used 80% efficient boilers. At the assumed boiler efficiency, the energy intensity of making soft-jelled candies is 4.9 kWh of gas/kg of product.

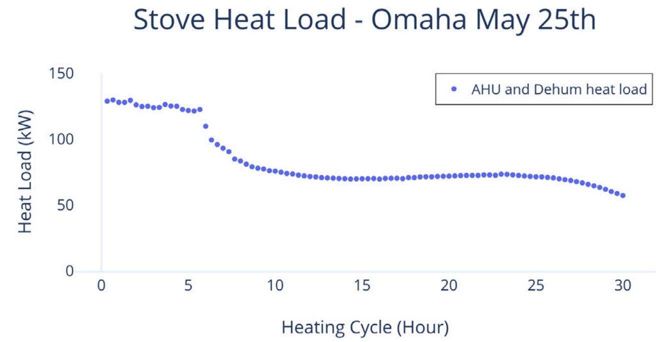

Fig. 7. May 25, 2017 Stove heating profile.

In addition to the heating requirement, air handler fans consume electrical energy. Carbon Trust found that electricity accounts for about 11% of the total stove energy requirement. While 11% is not insignificant, the electrical usage is significantly less than the gas. Because of the disparity between electrical and gas demand, this study focuses on optimizing gas consumption.

The stove heating requirement is most significant at the beginning of the cycle when the rate of moisture evaporation from the candy is highest. The heat required for the air handler and dehumidifier decreases as the stove progresses through the drying process. A heating load profile is shown in Fig. 7.

3.2. Optimal stove sizing

Four US cities in distinct climate zones, including Houston, Las Vegas, Salt Lake City, and Omaha, were investigated. The goal of the investigation was to minimize air handler energy, dehumidifier energy, and cost. The Pareto front of optimal solutions for each city was found using a MOEA. Each Pareto front consists of 100 optimal solutions, each of which cannot be improved upon without negatively impacting one of the objectives. The selection of the best solution is dependent on which objective is considered most important. For this case study, annual energy use and system first cost are considered the primary drivers. To select a solution, it is necessary to define a "base case" for which all solutions can be compared. For this study, the solution set with the lowest energy requirement is considered the "Base Solution." The percent reduction of initial cost and energy are summed, and the solution with the greatest reduction is selected as the proposed solution. This procedure searches for significant cost savings while minimizing the energy penalty. For example, in Omaha, the proposed solution reduces installation costs by 17%, and energy usage is only increased by 0.22% relative to the "Base Case".

Table 1 shows the climate data and optimal results for the proposed solutions. The hot-dry climate of Las Vegas is ideally suited for stove operation. Las Vegas has a low initial cost and requires significantly less energy to operate the stove. The most energy-intensive and expensive city to operate a stove is Houston. Operating the stove in Houston requires more dehumidification and, consequently, energy because the weather is consistently more humid. The proposed solution for each of the cities varies due to variation in the local climates. This study assumed a generic stove size of 16 m x 3 m x 4.8 m. The airflow rate found corresponds to 35–45 air changes per hour.

3.3. Climate impact

Air handler and dehumidifier energy are negatively correlated in Las Vegas, Salt Lake City, and Omaha; see Figs. 8, 9, 10, and 12. This negative correlation occurs because the stove can remove excess moisture evaporating from the candy in two ways. The first is by using a large amount of outside air to flush the excess moisture. The second is to use a smaller amount of dehumidified outside dry air to absorb moisture from the candy. When the stove primarily uses outside air to dehumidify, the air handlers bring in more outside air and, consequently, need to heat that outside air to the stove set-point point of 50 °C. Alternatively, the dehumidifier can remove moisture from the outside air before introducing it into the system. If the dehumidifier is running, the air handler heating load decreases, but the desiccant wheel's regenerative side requires more heat. The inverse energy relationship of the two systems results in a cost disparity, where decreasing the cost of one system increases the cost of the other system.

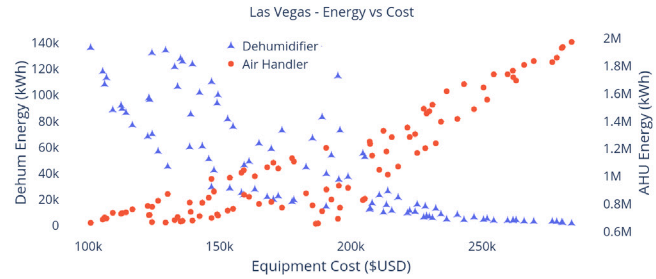

Fig. 8. Las Vegas — system energy vs cost.

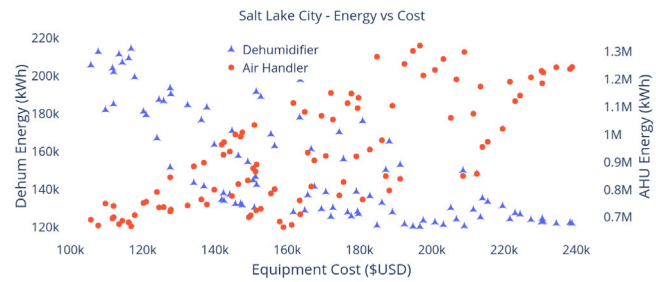

Fig. 9. Salt Lake City — system energy vs cost.

Houston is consistently warmer and more humid than the other cities assessed in this study. The high humidity in Houston requires more than double the amount of dehumidifier energy than the other cities; see Fig. 12. The warmer temperatures and latent heat gain across the desiccant wheel reduce the air handler energy by approximately 40%, but the total energy required is higher. The Houston solution space is more tightly grouped than the other cities assessed; see Fig. 11. Each of the solutions in Houston has a roughly balanced split between the air handler and dehumidifier energy.

Las Vegas has the hottest and driest climate analyzed in this study. Consequently, operating the stove in Las Vegas requires 11% to 15% less energy than the other cities.

It is dry enough in Las Vegas that it is possible to flush the moisture from the stove by introducing large quantities of outside air at a high air change rate. High volumes of outside air bring the dehumidification energy use to near zero, see Fig. 12. As the dehumidification energy approaches zero, the high-efficiency stoves operate like a traditional stove without dehumidification. When the stove is operating without dehumidification, the stove requires more energy in the hottest and driest climate when compared to the system using the desiccant dehumidifier in cooler and more humid climates. Table 2 shows the five most beneficial solutions for a stove in Las Vegas.

4. Discussion and 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

Table 1
Analyzed Cities Climate and Objective Results.

City/Climate Zone	DB (C)			RH			Air	OA	Cost	Energy
	Min	Max	Avg	Min	Max	Avg	kg/s	%	USD	MWh
Las Vegas/Hot-Dry	1	46	21.6	1.4	100	28.8	2.64	37	$100k	800
Salt Lake City/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	937

Table 2
Las Vegas Solution Space Sorted for Minimal Energy Use.

Air Flow kg/s	% OA	AHU Energy kWh	Dehum Energy kWh	Total Energy kWh	Total Cost USD	Total Cost % change	Total Energy % change	Total change
9.1	10	657,876	140,370	798,247	186,647	N/A	N/A	N/A
9.15	10.5	660,356	138,951	799,308	187,502	+0.46%	+0.13%	+0.59
2.64	37	664,212	136,229	800,442	100,880	−45.95%	+0.27%	−45.68%
4.77	20	666,650	134,224	800,875	129,434	−30.65%	+0.33%	−30.32%
5.15	19	674,916	135,134	802,703	135,134	−27.6%	+0.56%	−27.04%

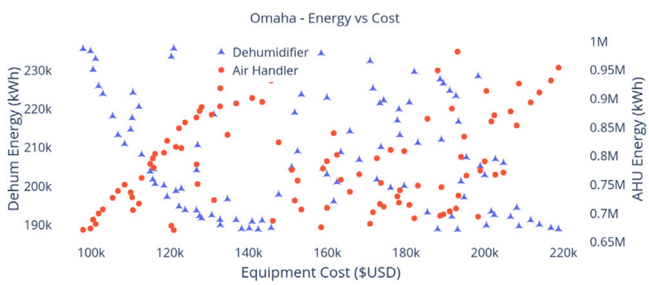

Fig. 10. Omaha — system energy vs Cost.

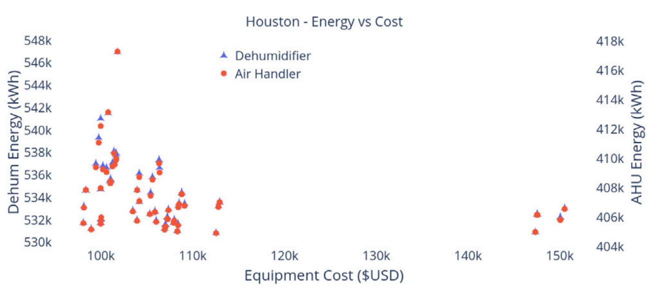

Fig. 11. Houston — system energy vs cost.

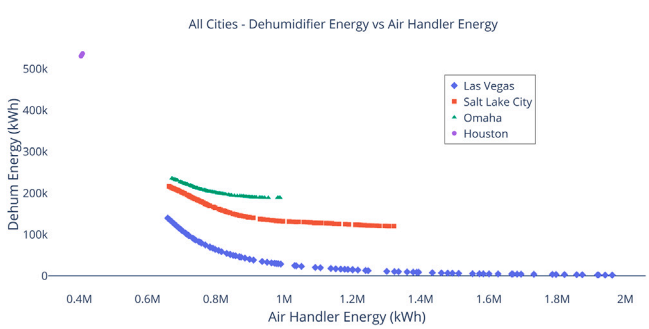

Fig. 12. All cities — Dehum energy vs AHU energy.

requires an energy intensity of 5.617 kWh/kg, a 12% difference. High-efficiency stove systems that use desiccant wheel dehumidifiers were evaluated and found that the energy intensity is reduced to 1.5 to 4 kWh/kg product. The local climate was shown to have a significant impact on energy usage. Operating a confectionery stove in a dry climate requires 15% less energy than operating a confectionery stove in a humid location. The high-efficiency stoves provided substantial energy savings regardless of the local climate. Confectionery facilities operate worldwide, and companies can significantly reduce energy usage by strategically considering the environment when planning where to build their next facility.

Finally, the stoving parameters were evaluated using an MOEA to find the optimal solutions 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%.

A generic model shows the energy consumption of a confectionery stove, but the approach described in this study can apply to any drying process. The energy model used drying curves for starch-based jellies (Sudharsan et al., 2004), but any drying curve could be substituted to model different types of candies. The model could be significantly improved and custom fit to specific processes by training neural networks to real-world process data to predict the drying curve. Furthermore, given that the exhaust air temperature leaving the stove can be up to 60 °C, there is an opportunity to recover the energy in the exhaust air stream. Future work could investigate capturing the waste heat with a heat pump system similar to Miah's heat integration approach (Miah et al., 2015). An interesting extension of the model defined in this work would be to use neural networks as a way to represent the moisture and heat loss from the candy during the drying process similar to work by Barzegar. Barzegar used artificial neural networks to develop predicted models for the drying of green beans (Barzegar et al., 2015). Oliveira conducted another recent study using artificial neural networks for modeling a drying process. Oliveira's study used an artificial neural network to model chewy candy drying in a vacuum drying chamber (Oliveira et al., 2008). The downside to using neural networks to model a drying process is that training the neural network requires extensive data that manufacturers are hesitant to share. However, if data is available neural networks can significantly improve the accuracy of the model.

A limitation of this work is that it focuses on initial investment cost and energy usage. When making actual siting decisions, there are other important factors to consider: energy rates, labor rates, tax incentives, and on-going maintenance costs. While important, these factors do directly correlate to the local climate. For example, the maintenance of stoving equipment is highly specialized, proprietary, and depends on individual company standards. Therefore, this paper addresses the important aspects of selectively siting facilities and optimizing system control parameters with consideration of the local climate to reduce initial cost and energy usage in favorable climates. Another opportunity for future work would be to optimally site a confectionery facility within a hot-dry climate by considering these additional criteria.

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 multiobjective evolutionary algorithm is used to optimize control parameters. The energy model is an improvement on current confectionery stove research because the prior work did not 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. Finally, 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.

CRediT authorship contribution statement

Gabriel Legorburu: Conceptualization, Methodology, Writing - review & editing, Visualization, Formal analysis. **Amanda D. Smith:** Writing - review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Dehumidifier equations

Dehumidifier Equations from Becalli Paper (Beccali et al., 2003)

$$X_{out} = \frac{(e^{0.053*Tout} * (0.9428 * UR_{reg} + 0.0572 * UR_{in}) - 1.7976)}{18.671} \tag{A.1}$$

$$\frac{UR_{out} * e^{0.053*Tout} - 1.7976}{18671} = \frac{(h_{out} - 1.006 * Tout)}{2501 - 1.805 * Tout} \tag{A.2}$$

$$UR_{out} = 0.9428 UR_{reg} + 0.0572 UR_{in} \tag{A.3}$$

$$h_{out} = 0.1312 * h_{reg} + 0.8688 * h_{in} \tag{A.4}$$

Energy balance on desiccant wheel. Energy change of process air stream is equal to energy change on the regeneration air stream.

$$((h_{in} - h_{out}) - (\frac{X_{in} - X_{out}}{1000}) * (2500 + Tout1.996)) = \tag{A.5}$$

$$((h_{reg} - h_{reg_out}) + (\frac{X_{reg_in} - X_{reg_out}}{1000}) * (2500 + Tout1.996)) \tag{A.6}$$

Water mass balance

$$X_{reg,out} = X_{in} + X_{reg,in} - X_{out} \tag{A.7}$$

Combination of relative humidity equation in Becalli paper (UR) and enthalpy equation of air to push humidity of regeneration air into the system of equations

$$UR_{reg} = (18.6715 X_{reg_in} + 1.7976) e^{-0.053*\frac{1000*h_{reg} - 2501 X_{reg,in}}{1.805 X_{reg,in} + 1006}} \tag{A.8}$$

Appendix B. Psychometric equations

$$\omega_{out} = \frac{(2501 - 2.326 * wb_{air,out}) \omega s_{out} - 1.006(db_{out} - wb_{air,out})}{2501 + 1.86 * db_{out} - 4.186 * wb_{air,out}} \tag{B.1}$$

Leaving air wet bulb temperature may be solved as a function of relative humidity and dry-bulb using Eq. (B.2) (Stull, 2011).

$$\begin{aligned} Twb_{air,out} = {} & (Tdb_{out} * atan 0.151977 * (100 * RH_{out} + 8.313659)^{0.5} \\ & atan(Tdb_{out} + 100 * RH_{out}) - atan(100 * RH_{out} - 1.676331) \\ & 0.00391838 * ((100 * RH_{out})^{3/2}) * atan(0.023101 * 100 * RH_{out}) \\ & - 4.686035) \end{aligned} \tag{B.2}$$

$$RH_{out} = \frac{pw_{out}}{pws_{out}} \tag{B.3}$$

$$\omega s_{out} = \frac{0.621945 * pws_{out}}{p_{total} - pws_{out}} \tag{B.4}$$

$$\begin{aligned} pws_{out} = {} & \exp \frac{c8}{Tdb_{out}} + c9 + c10 * Tdb_{out} \\ & + c11 * Tdb_{out}^2 + c12 * Tdb_{out}^3 + c13 log(Tdb_{out}) \end{aligned} \tag{B.5}$$

$$pw_{out} = \frac{p_{total} * \omega_{out}}{0.621945 + \omega_{out}} \tag{B.6}$$

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