OPTIMIZATION OF SYSTEMS AND OBJECTS

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Abstract: optimization means finding the best solution among several alternatives. Optimization can be performed an all engineering fields. There are two examples show the application opportunities at logistic systems. One of them is the traffic light control and the other one is a sugar drying system. Both of them show the efficiency and necessity of optimization to reduce waiting time and energy.

Keywords: optimization, logistic system, traffic light control, drying system.

1. Background of optimization

In the optimization process for an engineer it is important to know the behaviour of the system and the structure well. It is as important to have a reliable optimization technique to find the optimum.

In our practice on structural optimization we have used several techniques in the last decades. We have published them in our books and gave several examples as engineering applications (Farkas & Jármai [1., 2., 3.]). Most of the techniques were modified to be a good engineering tool in this work.

The general formulation of a single-criterion non-linear programming problem is the following

minimize $$f(x) \quad x_1, x_2, ..., x_N, \tag{1}$$

subject to $$g_j(x) \le 0, \quad \mathrm{j} = 1,2,...,P, \tag{2}$$

$$h_i(x) = 0 \quad i = P+1,...,P+M, \tag{3}$$

f(x) is a multivariable non-linear function, $g_j(x)$ and $h_i(x)$ are non-linear inequality and equality constraints, respectively.

In the last two decades some new techniques appeared e.g. the evolutionary techniques, like Genetic Algorithm, *GA* by Goldberg [4.], the Differential Evolution, *DE* method of Storn & Price [5.], the Ant Colony Technique (Dorigo et al. [6.]), the Particle Swarm Optimization, *PSO* by Kennedy & Eberhart [7.], Millonas [8], the Artificial Immune System, *AIS* (Farmer et al. [9.], de Castro & Timmis [10.], Dasgupta [11.] and the response surface technique Egorov [12.]. Some other high performance techniques such as Leap-frog with the analogue of potential energy minimum (Snyman [13.]), Snyman-Fatti method [14.] and the Harmony Search technique have also been developed.

2. Traffic light control optimization

The first application is the traffic light control optimization. Can we optimise for all conditions? Is a determined optimum is useful in other circumstances? In a complex city road system, which is populated with various road users the relations between traffic control and commuters are very important. Physical detection of passing road users and improved traffic light control algorithms are to be combined to optimize traffic flow. At a given infrastructure one cannot pre-set the algorithm to all possible road combinations. The aim of the controller program is to detect the number of road user, the traffic situation and to implement an optimization to reduce waiting time. Different driving policies and different control techniques are shown in the Green Light District program [15.]. We have used the program to evaluate and control the Zsolcai gate district traffic in Miskolc and made comparisons with parametric investigations.

Traffic in a city is very much affected by traffic light controllers [16.]. It may happen that one is waiting for a red light when all the other drive lanes are free of traffic. Firstly one has to model an infrastructure of a city, secondly the behaviour of different road users must be able to be simulated and thirdly on all intersections where traffic lights are active, there can be made active and evaluated a certain traffic light controller [17.]. The interaction between road users and traffic lights in a situation leads to certain waiting times (or travel times) of road users. By conducting experiments with the simulator these times can be measured and optimized [18]. Since unnecessary waiting can be frustrating, there is research going on *to make traffic controllers more intelligent*. This can be done in different ways:

(1) the use of better sensors to asses the traffic situation,
(2) the use of optimization algorithms for traffic light given a certain realistic traffic situation.

At the traffic simulator there are three factors play an important role:

(1) the program must be generic enough to model the infrastructure of different cities,
(2) the simulation must be able to simulate the behaviour of different types of road users, of course cars must drive to a destination, but it should also be possible to simulate bikes, pedestrians and busses,
(3) by running simulations one has to be able to find differences in the traffic light algorithms performance. These differences much be expressed in average waiting times for a vehicle.

Road users have a certain starting point and a destination. They follow a route to travel from the beginning to the end. This route can be calculated by a shortest path algorithm, but also can be learned by a learning algorithm. Traditional light controllers use an algorithm to determine which lights to set to green for a certain time, after which other lights get set to green etc.

Among the different types of algorithms there are some self leaning algorithms, which seem to get the best results. These algorithms make use of the knowledge of how many cars are waiting at each traffic light. The learning algorithms learn from the advantage to be gained (expressed in the amount of lowered total waiting time) to set certain lights to green. At the hand of the test results one can see what controller works best and which traffic situations gives the best result. Non-learning algorithms are also available, to make comparisons possible.

Road users choose their next lane when crossing a junction so to minimize probable waiting time at the next junction. If a next lane has traffic lights, a co-learn value is requested from the traffic light control algorithm, if it is the kind to compute co-learning values. Along with

this the road users sends a value for itself to the controller so other road users may benefit from it.
Co-learning will greatly improve the distribution of road users on a map with many possible shortest paths (say, a grid-like infrastructure), but will have little effect if there are few possibilities or the traffic load is too high to distribute much.
All intersections are assumed to be equal, i.e., there are no main roads in the network where the traffic lights have a higher priority.
Traffic jam is the most extensively studied traffic phenomenon. Traffic jams can emerge because of various different reasons. Most often traffic jams are observed at bottlenecks, e.g. lane-reductions or crossings of highways. At bottlenecks the capacity of the road is locally reduced thereby leading to the formation of jams upstream traffic. Downstream the bottleneck, typically, a free-flow region is observed. In addition, traffic accidents, which also lead to a local reduction of the capacity of the highway, can give rise to traffic jams.
At the University Utrecht they have developed an Intelligent Traffic Light Control System [15.] which was applied and slightly modified by us.

2.1 Driving policy

Road users condense at an edge node with the intention of reaching another node. For this purpose they must follow the roads that comprise a minimum distance to that node. These paths are either pre-calculated after map creation or learned during simulation. Learning yields best results for complex maps where no best setting is evident, but is demanding on the hardware A driving policy will point a road user every time a decision has to be made to a lane, which is not full, is reachable by following the direction rules, and brings the road user closer to its destination.
Driving policies have less influence on the flow of traffic than traffic light controllers, because in keeping with realistic possibilities, drivers know less about the status of a city than a centralized traffic light control. Optimizing values locally in regard to the adjacent lanes is always less effective than taking into account the whole environment, but is currently more realistic. Advances in car communicational systems that give a driver an overview of the traffic density in the area should give quite different results.

2.2 Reinforcement learning

Reinforcement Learning (RL) enables an agent (for example a car) to learn from interacting with an environment through a trial and error process and learn for the obtained feedback. It can be used to control an agent who has to solve a particular task in an environment. Examples are learning to play games, robot control, elevator control, and network routing. Important issues are exploration to gather interesting experiences for the agent, function approximation to generalize over experiences, multi-agent reinforcement learning, and solving partially observable Markov Decision Problems.
In reinforcement learning the transition P and reward functions R are a-priori unknown. Therefore, the agent has to learn a policy by interacting with the environment that provides feedback about the goodness of particular state-action pairs. Reinforcement learning algorithms usually learn to update the Q-function after each performed action.

2.3 The basic cycle of a reinforcement learning agent is:

1. Perceive the current state: $s_{,t}$
2. Use the policy to select an action: $a_t = \pi(s_t)$,

3. Receive a reward r_t and examine the new state s_{t+1} after the action was performed,
4. Update the Q-function (the action evaluation function) using the information (s_t, a_t, r_t, s_{t+1}),
5. Set $t = t + 1$.

Usually, the Q-function is initialized to all zero-values, and therefore the initial policy is completely random. By exploring the results of actions, and learning the best (current) policy from these, the reinforcement learning agent stochastically improves its behaviour.

2.4 Q-learning

Several reinforcement learning algorithms exist. The most commonly used algorithm is *Q*learning [19]. *Q*-learning does not use a model of the environment and updates the Q-function after each step using the following equation:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha(r_t + \gamma V(s_{t+1}) - Q(s_t, a_t)) \tag{4}$$

where $0 < \alpha < 1$ is the learning rate, V is the maximum of Q. If the learning rate is decreased after each time-step in a specific way, and all state-action pairs are tried infinitely often, the use of Q-learning converges to the optimal Q-function and policy for Markov decision problems.

2.5 Evaluation tools

The data collected from running a simulation on a map can be displayed and analyzed in a number of ways:

- In-view statistics can be toggled on, which will colour junctions to indicate the average waiting time there. The darker the colour, the longer road users have to wait there.
- largest waiting queue, with the id of the junction,
- largest average junction waiting time, with the cycle count,
- total number of road users arrived, with count.

2.6 The statistics window contains precise data on the current simulated map

- list of edge nodes with id, arrived road users, current queue length, average trip time, and average trip waiting time o list of junctions with id and average junction waiting time (best to be overviewed by toggling in-view statistics,
- totals of number of road users arrived, current queue length, average trip time, average waiting time and average junction waiting time,

A tracking window to track one of the following:

- total waiting queue length,
- average trip time,
- average trip waiting time
- average junction waiting time.

2.7 Application of the program for the city Miskolc [20]

Figure 1 shows an application of the program for the city Miskolc at Zsolcai gate district. We consider that 500 cycles equal to 1 hour. At nodes 9 and 7 (main end nodes) the output frequency for car is 0,05 and for bus is 0,01. The random algorithm shows the relatively long queues and waiting times. Regarding the stating point to be midnight, at 6 o'clock in the morning we get following result shown on Figure 1. At the other nodes the frequency set as 0,001 for car and 0,0001 for bus.

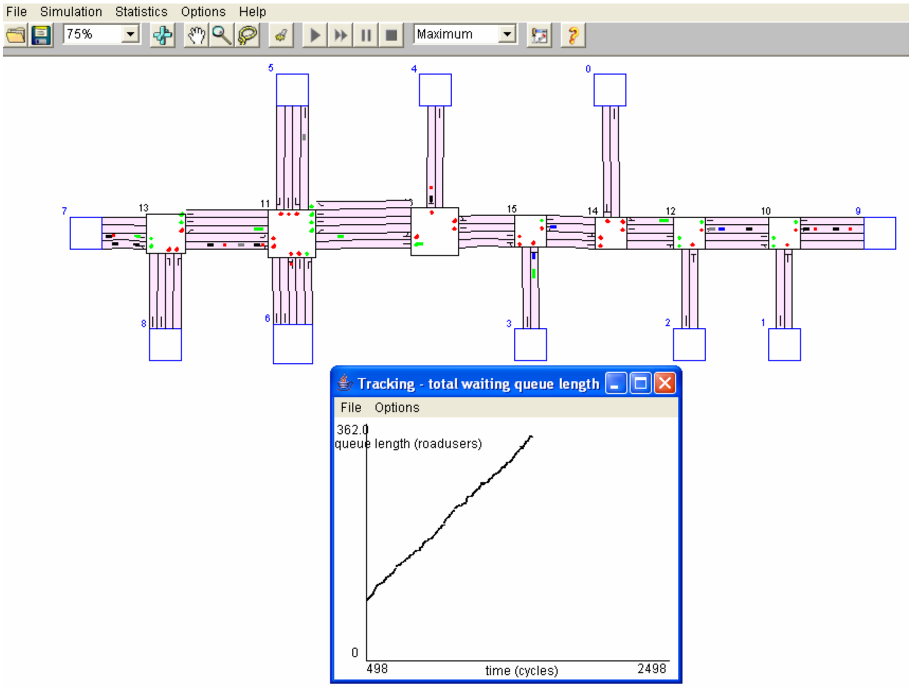

Figure 1. Entrance of Miskolc at Zsolcai gate district, the traffic system using Random algorithm between 0 – 6 am.

On Figure 2 the traffic jam is visible from 6 to 9 am. (4500 cycles) using Random algorithm. Random algorithm mean a randomly controlled system, so it be regarded as uncontrolled. The two main edge nodes output capacity are 0,2 for car, 0,04 for bus. At other nodes 0,01 for car, 0,001 for bus. The increment of queue length is visible.

On Figure 3 the cleaning the road system form the traffic jam is made by Genetic algorithm type ACGJ-3. The new control system solves the problem. Genetic algorithm is very popular in optimization, since it can solve non-convex problems [4].

Genetic algorithm has its own limits at a given road system. If we increase the number of road users, non of the algorithm can avoid traffic jam. The two main edge nodes output capacity in this case are 0,8 for car, 0,01 for bus (8000 cycles). The only solution is to decrease the road users. In daily life the traffic jam in the morning can be cleaned by the control algorithm when later the users are less.

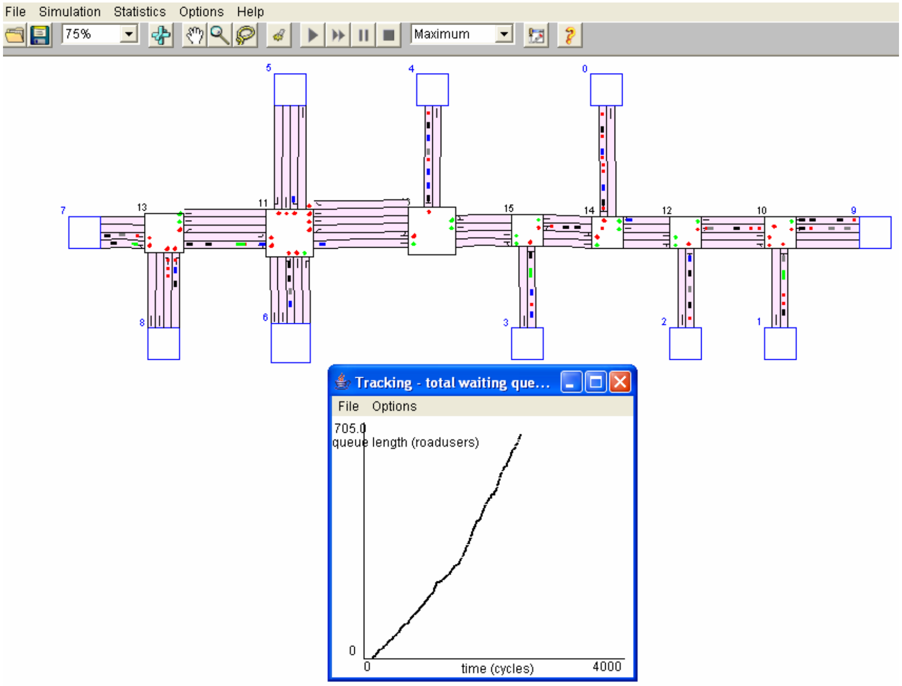

Figure 2. Entrance of Miskolc at Zsolcai gate district, the traffic system using Random algorithm between 6 – 9 am.

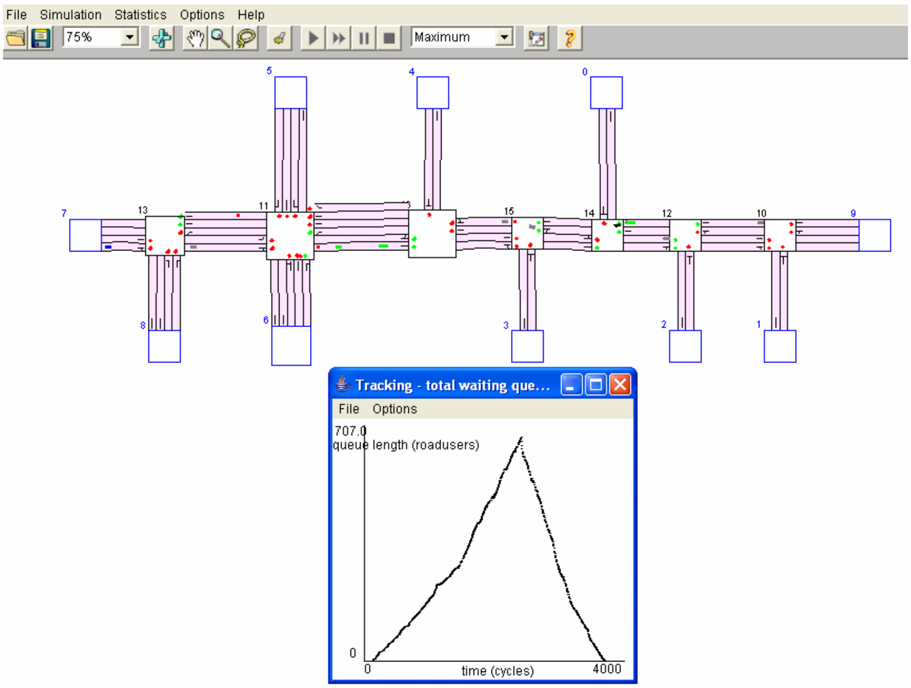

Figure 3. Entrance of Miskolc at Zsolcai gate district, cleaning the traffic system using Genetic algorithm between 6 – 9 am.

3. Sugar drying system optimization

At various industrial fields there can be found those equipment, systems, which work properly, but their service is not optimal. They do not save material and energy. Checking their service we can elaborate some control possibilities for the existing equipment, which lead to safer service using less energy and material. In this paper we investigate the operation of a Roto-Louvre-type drier cylinder. The purpose of the drier is drying and cooling sugar. The investigation consists of two phases: the first is to build a simplified global heat engineering model describing the service of the drier. This model makes it possible to find relation between dried material and the air-flows making drying and cooling. On the other hand this heat engineering model was built into an optimization algorithm, where the scope was to minimize the total used energy. The optimization makes it possible to find the energy minima when several input and output parameters are changing.

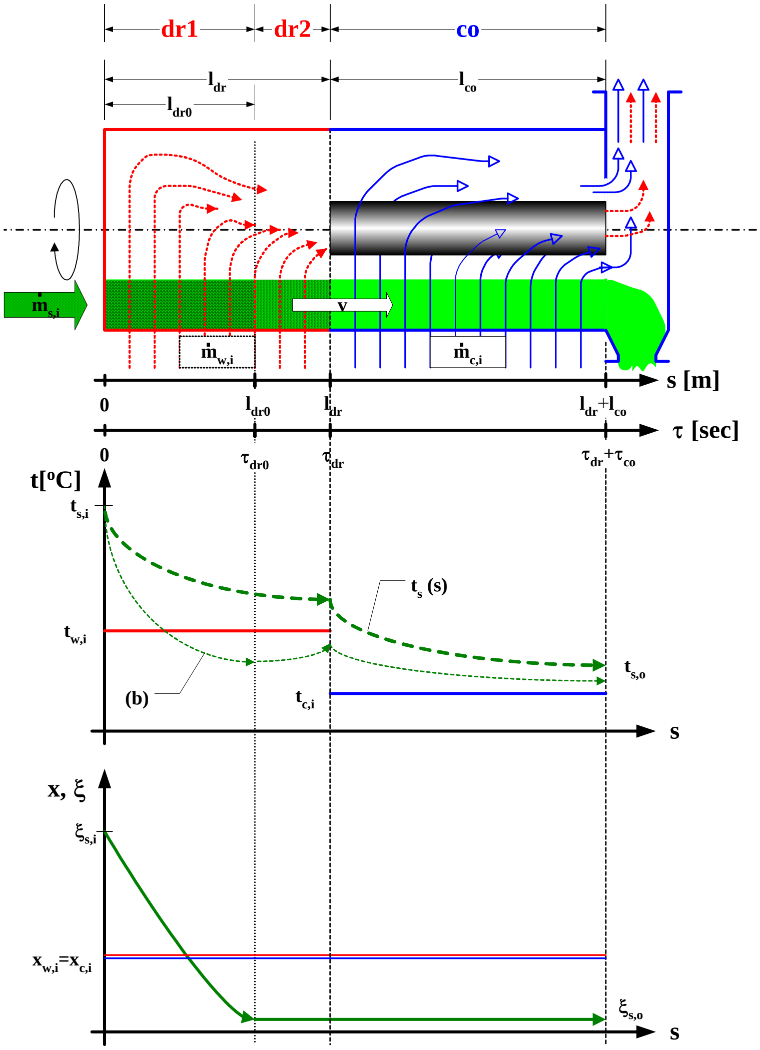

Figure 4. The service of a Roto-Louvre-type drier cylinder for sugar

As an example we have calculated the service optima considering various outside air temperatures (varying in a wide range). Both global heat engineering model and optimization technique are applicable finding optimum service conditions for drying other materials.
The service of a Roto-Louvre-type drier cylinder for sugar can be seen in Figure 4. The feeding of wet sugar is at the left side of the circulating drier. The movement of the sugar is in axial direction, while on the lower bottom of the drier cylinder bin through special holes warm and cold air is blown into the cylinder, through the sugar layer. First the sugar is in contact with the warm air, gives the surface humidity to the air, while its temperature is decreasing. Moving the sugar toward, there are cold air is blown into the cylinder, through the sugar layer. The result is the decreasing of the sugar temperature, its degree of humidity practically constant.

3.1 Heat engineering model of drier cylinder

Our aim was to elaborate that kind of model, where we can find connection between the parameters of incoming and outgoing sugar and the volume and temperature of warm and cold air. Finding these equations we can control the process and build into the optimization algorithm.
Main features of the heat engineering model:

- We assume the cylinder to be heat insulated, neglecting heat loss during the process.
- We have built a global model, so we do not consider chancing of drying in time and place. *(Our empirical results showed that the drier cylinders are usually over-designed, it means that the sugar looses most of its surface humidity at the first half of the drier (dr1) as it shown in Figure 4. We have elaborated a detailed heat engineering model for design of driers (Szabó [21.]). For the optimization, described below, the global model was applicable. In this case the main scope was not the analysis of the processes in the drier).*
- In the model the drying and cooling phases are separated.

On Figure 5 the chancing of degree of humidity is visible.

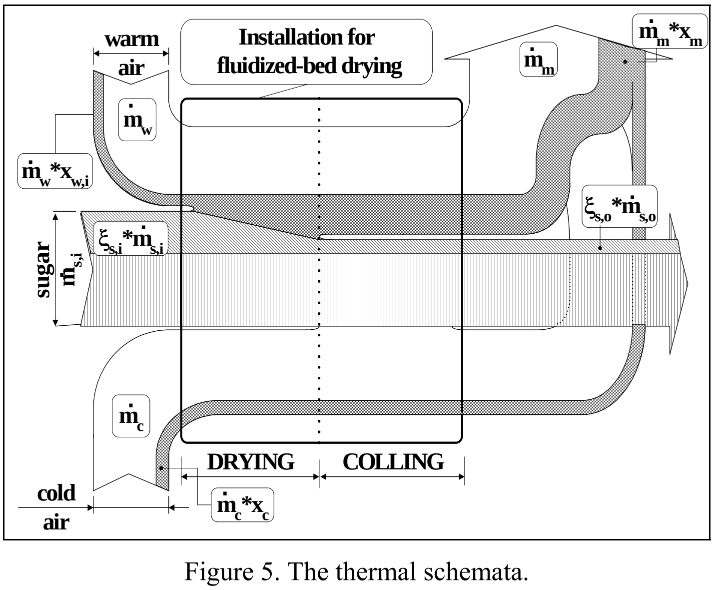

Figure 5. The thermal schemata.

The incoming $\dot{m}_{w,i}$ volume of warm air and the $\dot{m}_{c,i}$ volume of cold air humidities are $x_{w,i}$ and $x_{c,i}$ respectively. So the necessary dry air volumes are:

$$\dot{m}_w = \dot{m}_{w,i} \cdot \frac{1}{1 + x_{w,i}}, \qquad \dot{m}_c = \dot{m}_{c,i} \cdot \frac{1}{1 + x_{c,i}} \tag{5}$$

3.2 Drying phase

In the drying phase the incoming wet and hot sugar meets with the warm air arriving at the drier cylinder bin surface. The air takes the surface humidity of the sugar. The evaporating humidity means taking heat energy from sugar cause thermal decrement at sugar-air mixture (Imre [22]). When evaporation ended before the end of the drying phase there can be temperature increment at the sugar, depending on the temperature of sugar and warm air . This process is shown on the first diagram of Figure 4.
At the drying phase we assume the followings:

- At the end of the drying phase the temperature of the sugar-air mixture is equal, its value is the following

$$t_1 \cong t_{s,o} \cong t_{w,o} \,. \tag{6}$$

- At the end of the drying phase the sugar has lost its surface humidity, so its degree of humidity is decreasing to the inner one

$$\xi_1 = \xi_{s,o} \tag{7}$$

(Vice versa the drying warm air degree of humidity is increasing to a value $x_1 = x_{w,1}$*).*

3.3 Cooling phase

In the cooling phase the sugar, which has lost its surface humidity is in contact with the cold air. In this phase we assume the followings:

- At the end of the cooling phase the temperature of the sugar-air mixture is equal, its value is the following

$$t_2 \cong t_{s,o} \cong t_{c,o} \,. \tag{8}$$

- At the cooling phase the degree of humidity of the sugar is constant, its value is $\xi_{s,o}$. It means, that the degree of humidity of the cold air also constant, its value is x_c.

3.4 Air mixture after drier cylinder

Air from drying and cooling phases mix leaving the drier cylinder. Equations for this mixture are the followings:

- Humidities:

$$(\dot{m}_w + \dot{m}_c) \cdot x_m = \dot{m}_w \cdot x_1 + \dot{m}_c \cdot x_c \,. \tag{9}$$

- Heat energy values:

$$\begin{aligned}&\left(\dot{m}_w+\dot{m}_c\right)\cdot\left[c_{p,m}\cdot t_m+x_m\cdot\left(c_{p,st}\cdot t_m+r_o\right)\right]=\\&=\dot{m}_w\cdot\left[c_{p,w}\cdot t_1+x_1\cdot\left(c_{p,st}\cdot t_1+r_o\right)\right]+\dot{m}_c\cdot\left[c_{p,c}\cdot t_2+x_c\cdot\left(c_{p,st}\cdot t_2+r_o\right)\right]\end{aligned}\quad. \tag{10}$$

3.5 Heat engineering calculation

We can establish a calculation process, finding the connection between incoming and outgoing materials volumes and qualities. Calculation is made, what are known properties, what are unknowns. In this specific case we describe a calculation, which is important to practice and where the degree of humidity of the outgoing sugar is prescribed with a value $\xi_{s,o}$. The volumes and the quality of the incoming sugar and air are given. Unknowns are the outgoing sugar and air humidity and temperature.

3.6 Optimization of the drying process

Considering the previous heat engineering assumption, our aim was to solve drying and cooling of sugar, coming from centrifuge, using the least energy possible. This process is going on with the outside air, according to the outside conditions (Jármai & Szabó [23.]).
Investigate the problem in details. The drying and cooling air-moving is made by three ventilators, in the warm-air-line a heat exchanger produces warm air. The scheme of the system is visible on Figure 6. The three ventilators and the steam heating form an energy system. The task is to optimize the service of this system. The minimum energy consumption can be determined for the drying process due to the volume and degree of humidity of the incoming sugar and the quality of the outside air. We should find the optimum warm and cold air volume and the necessary temperature of the warm air. Solving this problem the characteristic lines of the ventilators $\Delta p_t(q)$ and $\eta(q)$ are known, which belong to air temperature T_a=20°C. We assume, that the $\Delta p_t(q)$ characteristic lines depend on the behaviour of the transported gas on a known way, but the $\eta(q)$ characteristic lines are independent from the gas condition.

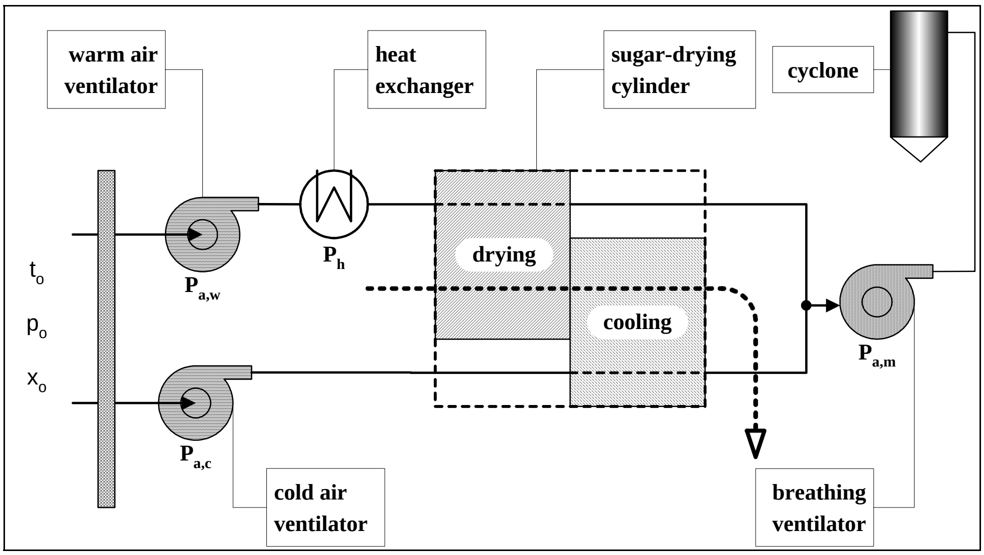

Figure 6.

We are looking for the minimum of the total power [24.]:

- Given parameters:
  - t_o, p_o, x_o, i.e. state of the environment, the drying-cooling air comes from,
  - $\dot{m}_{s,i}$, $t_{s,i}$, $\xi_{s,i}$, i.e. behaviour of the incoming sugar.
- Prescribed:
  - $\xi_{s,o}$, i.e. the allowable degree of humidity of the sugar at storage.
- Variables:
  - t_w, q_w, i.e. temperature and volume of warm air, for which there are limits given:
    - $t_o \leq t_{w,i} \leq t_{s,i}$,
    - $q_{w,\min} \leq q_w \leq q_{w,\max}$ *(good efficiency service region of the ventilator).*
- Constraints:
  - q_c, q_m, i.e. those quantities, for which there are limits given:
    - $q_{c,\min} \leq q_c \leq q_{c,\max}$ *(good efficiency service region of the ventilator),*
    - $q_{m,\min} \leq q_m \leq q_{m,\max}$ *(good efficiency service region of the ventilator).*

The equations above were built into the Rosenbrock's Hillclimb optimization algorithm (Farkas & Jármai [1.]). This can be made easily with a small correction of the calculation. Optimization can be made in different conditions. We can investigate the drying process due to different degrees of humidity of the incoming sugar. Chancing the capacity of the drying cylinder, i.e. the volume of the incoming sugar we can investigate its effect on the process. In our example we have investigated how drying process chancing with the outside air temperature. This is an interesting problem in sugar beet treatment. This is a campaign in autumn and at the beginning of winter. The outside temperature can be relatively high in this period of the year and when winter comes, it is very cold sometimes.

Our investigated example is as follow:

- conditions of the environment:
  p_o=1,038 *bar*, φ_o=61.3% , the temperature is between $-10^oC \leq t_o \leq 23^oC$;
- the incoming sugar volume, temperature and degree of humidity:
  $\dot{m}_{s,i} = 11{,}4$ *kg/s*, $t_{s,i}=55^oC$, $\xi_{s,i} =$ 6,8*g/kg ;*
- the prescribed temperature and degree of humidity of the outgoing sugar:
  $t_{s,o}=32^oC$, $\xi_{s,o}$ =0.15*g/kg ;*
- the limits are as follows:
  $t_o \leq t_{w,i} \leq t_{s,i}$, 4 $m^3/s \leq q_w, q_c \leq 10\ m^3/s$, 8 $m^3/s \leq q_m \leq 16\ m^3/s$.

We have determined the optimum process to a given temperature t_o which vary on a given range. The results can be found on Figure 7. On the horizontal axes of figure there is the temperature of the environment. On Figure 7 the changing of cold and warm air volume flow can be seen.

Conclusion

The examples show, that optimization is useful in logistic system design. The program is able to evaluate the traffic control system of a city and to optimize traffic lights. Using different inputs of road users, we can simulate the different situations during a day. We made comparisons using Random technique and the Genetic algorithm, to optimise the traffic flow. With this technique one can reduce the waiting queue, time and the consumed fuel, saving a lot of money and increase the capacity of the road system.
For the sugar drying system it is visible, that for the given parameters the drying and cooling can not make with air temperature greater than $t_o=23^oC$, because the induction ventilator volume flow q_m would be greater than its limit capacity $16m^3/s$. The cold air ventilator volume flow q_c has also reached its upper limit $10m^3/s$ at 22°C temperature. From the figure it is visible, that for $t_o<15^oC$ temperature the volume flows q_c and q_m are at the lower limit $4m^3/s$. This shows the overdesign. Less volume flow is not possible, because practical experiences show, that this volume flow is necessary for fluttering and mixing sugar. Temperature changing is a characteristic behaviour, that due to temperature $t_o<15^oC$ cooling is necessary, the temperature of incoming warm air $t_{w,i}$ should be greater then temperature of the environment $t_o=t_{c,i}$. On this figure both drying air temperature t_1 at the end of the drying

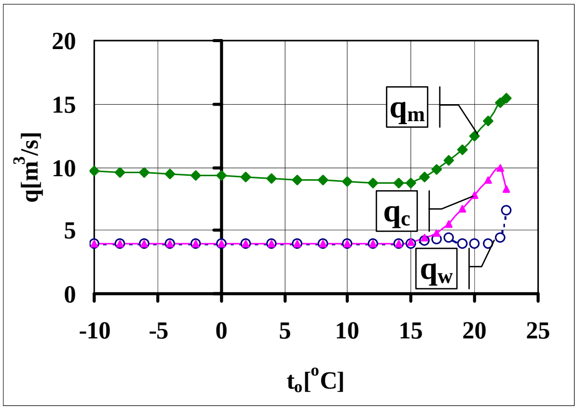

Figure 7. The changing of air volume flow.

phase and outgoing air temperature t_m are marked. The three ventilator total power is the following

$$P_{vent} = P_{a,w} + P_{a,c} + P_{a,m}$$

heating power is P_h and the addition of these two powers is P_t . It is visible, when there is heating of air is going on, its power is significant, because of its nominal value. We can calculate the behaviour of the sugar, the energy consumption of the system. Optimizing it we could find minimum energy consumption.

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