Trends in

Contemporary Engineering Sciences

Editor: Yoel Tenne

Ariel University, Israel
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1 Introduction

Problems in engineering and science often require the optimization of an objective function. As the complexity of problems increases, for example, with an increasing number of variables or local optima, classical optimization algorithms tend to struggle [15]. This has motivated the application of heuristic and often nature-inspired approaches and one of the widely used ones are the evolutionary algorithms (EAs) [3]. They have shown to be effective across a range of problems and their relative simplicity assisted in their prevalent application.

However this relative simplicity also results in a slower convergence since function information is not effectively used as with other techniques such as the gradient based methods. The slower convergence requires more function evaluations which is particularly challenging when function evaluations are computationally expensive [15]. To address this issue this study proposes an enhanced evolutionary algorithm (EA) framework in which convergence is accelerated based on a new concept of monitoring the trajectory of the centroid of the EA population. The process is invoked every several generations and and centroid of the next iteration is interpolated based on accumulated data without requiring an additional full evolutionary loop. Numerical experiments across varied test functions show the effectiveness of the proposed method. The remainder of this chapter is organized as follows: Section 2 provides the background information, Section 3 describes the proposed method, and Section 4 describes numerical tests performed to evaluate the proposed method. Lastly Section 5 concludes this chapter.
2 Background

EAs have been extensively used for solving challenging optimization problems ranging from structural design [16] to control systems [10]. A standard EA uses the operators of selection, recombination, and mutation in succession to explore the search space and identify better solutions. Since gradient information is not used convergence is often slow and requires a large number of function evaluations to obtain a satisfactory solution which is a challenge in many real-world problems [8, 6, 12, 14].

As such various modifications have been explored to accelerate the EA convergence. One approach is to combine the baseline EA with local search methods which results in a hybrid or memetic algorithm [13, 9]. This approach has also been extended to hybridization with other heuristic methods for example simulated annealing or particle swarm optimization [1, 18]. Another approach is to monitor the population diversity and ensure it is adequate so that exploration is preserved. In [5] the authors combined an EA with a clustering algorithm to identify similar offspring and then allow only those which are sufficiently different to progress, in an effort to improve diversity. In [7] the authors combined clustering with neural networks to further reduce function evaluations by avoiding evaluations of similar offspring. Also, in [17] the authors applied diversity preservation methods in a particle-swarm optimization algorithm.

While the above mentioned approaches were shown to improve EA convergence they do use only use information from the current iteration and ignore past information which has been obtained during the search, often at a high computational cost. Leveraging on this inefficiency the proposed method uses recent information to improve the convergence rate as explained in the following section.

3 Proposed Method

The proposed method is comprised of an EA followed by an approximation step. No restriction is made on the EA variant and in this study an EA which is representative of many others in the literature was used. It begins by generating a random sample of vectors and then its main loop begins. The population is ranked based on its fitness and parents are selected by stochastic universal selection (SUS). They are then uniformly recombined with probability 0.7 and mutated based on the Breeder genetic algorithm operator with probability 0.1 [2]. The population size $s$ was 20 and the number of generations was $(100 \times d)/s = 5d$ where $d$ is problem dimension. Algorithm 1 gives a pseudocode of the implemented EA.

As mentioned the convergence acceleration component operates by moni-
sample an initial population;

\textbf{repeat}
\begin{itemize}
  \item rank population by fitness;
  \item select parents (stochastic universal selection);
  \item recombine parents (uniform crossover);
  \item mutate offspring (Breeder genetic algorithm operator);
\end{itemize}
\textbf{until} until max generations;

\textbf{Algorithm 1}: The EA implemented.

storing the EA population in recent iterations. Specifically, the centroid of the best \( p \) percent of the population is calculated

\[
c_i = \frac{\sum x_j}{s \cdot p}
\] (1)

and recorded, where \( p \) is user-prescribed and \( s \) is the population size. Every \( n \) iterations a least-squares fit (LSF) polynomial is fitted based on the stored centroid and a different polynomial is fitted to each coordinate \( x_1 \ldots d \). Afterwards the centroid in the next iteration is interpolated by evaluating each polynomial at the \( n + 1 \) position. The polynomials coefficients are obtained by minimizing the sum of squared error

\[
E = \sum \left( \hat{f}_i - f_i \right)
\] (2)

\[
\frac{\partial E}{\partial a_j} = 0, \ j = 1 \ldots n
\] (3)

which results in a set of linear equations

\[
M a = r
\] (4)

where \( M \) is a matrix of terms based on the interpolating points, \( a \) is a vector of the polynomial coefficients and \( r \) is a vector based on the point indexes and centroid coordinate. For example, for \( n = 2 \) the resulting equations are

\[
\begin{pmatrix}
  n & \sum i & \sum i^2 \\
  \sum i & \sum i^2 & \sum i^3 \\
  \sum i^2 & \sum i^3 & \sum i^4
\end{pmatrix}
\begin{pmatrix}
a_0 \\
a_1 \\
a_2
\end{pmatrix}
= 
\begin{pmatrix}
\sum i \\
\sum i x_i \\
\sum i^2 x_i
\end{pmatrix}
\] (5)

which yield the coefficients of the fitted polynomial \( \hat{f}(x) = a_2 x_i^2 + a_1 x_i + a_0 \).

The process is repeated for each coordinate.

After obtaining the interpolated centroid the baseline population is updated by adding to each of its members the vector difference \( c_{n+1} - c_1 \) where \( c_1 \) is the centroid of the first population recorded in the set \( 1 \ldots n \). Thus the vectors are shifted in the direction in which the population is converging towards an optimum while achieving potentially similar progress but with fewer
generations. After updating the population the new vectors are re-evaluated, the cache of recorded centroids is cleared, and the process resumes. The algorithm terminates when the number of function evaluation has reached the prescribed limit or other common convergence criteria are satisfied.

To visualize how the method operates Figure 1 shows an example applied with the Rosenbrock function. The settings used were $n = 4$ and $p = 0.5$, namely, the update was performed every 4 generations and centroid was calculated based on the top 50% vectors in the population. Figure (a) shows the baseline population and the shifted one obtained after the update while figure (b) shows the trajectory of the centroid over 4 iterations and the resultant interpolated centroid obtained by a 3rd order LSF polynomial based on 4 centroids. To conclude this section Algorithm 2 gives a pseudocode of the proposed framework. The linear equations system for calibrating the polynomials coefficients is

\[
\begin{pmatrix}
  n \sum_i \sum_i \sum i^2 \sum i^3 \\
  \sum_i \sum i^2 \sum i^3 \sum i^4 \sum i^5
\end{pmatrix}
\begin{pmatrix}
  a_0 \\
  a_1 \\
  a_2 \\
  a_3
\end{pmatrix}
= 
\begin{pmatrix}
  \sum_i ix_i \\
  \sum i^2 x_i \\
  \sum i^3 x_i
\end{pmatrix}
\]

The method requires only two user-prescribed parameters: $n$ the number of generations to interpolate across and $p$ the percentage of best vectors in the population on which the centroid will be computed. Numerical experiments have been performed to study the impact of these parameter as explained in Section 4.
sample an initial random population;
\begin{verbatim}
repeat
    rank population by fitness;
    select parents;
    recombine;
    mutate;
    compute and store centroid of the best \( p \% \)s population vectors;
    foreach \( n^{th} \) generation do
        interpolate next centroid based on \( n \) stored centroids;
        compute centroid change \( c_{n+1} - c_1 \);
        update current population based on centroid change;
        re-evaluate the population;
    end
until max generations;
\end{verbatim}

Algorithm 2: The proposed algorithm.

4 Numerical Experiments

4.1 Sensitivity Analysis

As mentioned in Section 3 the proposed algorithm relies on two user-prescribed parameters: \( p \) - the percentage of top vectors by which the centroid is calculated and \( n \) iterations interval at which the update is performed. To study how these impact performance a set of numerical experiments has been conducted with different settings in a \( 2^n \) full factorial design of experiments where of the parameters was tested in low and high settings: \( n = 2, 4 \) and \( p = 0.4, 0.8 \) which results in 4 combinations. Each combination was applied across four established test functions [11] with 10 repetitions resulting in a total of \( 4 \times 4 \times 10 = 160 \) runs.

Table 1 gives the resultant test statistics from which it follows that the best results were achieved with either \( n = 2, p = 0.4 \) followed closely by \( n = 2, p = 0.8 \). Since both in both are equivalent the former settings were used in the benchmarking tests.

4.2 Benchmarking

For a thorough evaluation the proposed method was applied to an established set of test function [11] which includes the Ackley, Griewank, Rastrigin, Rosenbrock, and Powell functions in dimensions 5 and 10. To assess the performance gains the algorithm was benchmarked against a baseline variant (denoted Baseline) which is identical in operation but excludes the convergence acceleration step. For each test function–algorithm combination 30 runs were done (for an
<table>
<thead>
<tr>
<th>Function</th>
<th>Statistic</th>
<th>$n=2, p=0.4$</th>
<th>$n=4, p=0.4$</th>
<th>$n=2, p=0.8$</th>
<th>$n=4, p=0.8$</th>
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<td>7.761e+00</td>
<td>1.025e+01</td>
<td>1.033e+01</td>
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<tr>
<td></td>
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<td>1.859e+02</td>
<td>5.138e+02</td>
</tr>
</tbody>
</table>

SD is standard deviation. Best mean is emphasized.
Tables 2 and 3 show the resultant statistics from which it follows that in the lower dimensional test \((d = 5)\) the proposed method with \(n=5, p=0.4\) performed best in 3 out of 5 cases (Ackley, Griewank, Rastrigin) while in the higher dimensional cases \((d = 10)\) it outperformed the other variants in the Ackley, Powell and Rosenbrock functions. Overall the proposed method improved the convergence speed in 6 out of 10 cases and performed well across varied tests functions both in low and high dimensional problems.

To visualize the behaviour of the three algorithms benchmarked Figure 2 shows representative convergence plots from tests with the Ackley-05 and Powell-10 functions. It follows that the proposed method \((n=2,p=0.4)\) converged faster which further emphasizes it merit.

<table>
<thead>
<tr>
<th>Function</th>
<th>Statistic</th>
<th>(n=2,p=0.4)</th>
<th>(n=2,p=0.8)</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ackley-05</td>
<td>Mean</td>
<td>7.761e+00</td>
<td>1.033e+01</td>
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<td>Griewank-05</td>
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adequately large sample). Tables 2 and 3 show the resultant statistics from which it follows that in the lower dimensional test \((d = 5)\) the proposed method with \(n=5, p=0.4\) performed best in 3 out of 5 cases (Ackley, Griewank, Rastrigin) while in the higher dimensional cases \((d = 10)\) it outperformed the other variants in the Ackley, Powell and Rosenbrock functions. Overall the proposed method improved the convergence speed in 6 out of 10 cases and performed well across varied tests functions both in low and high dimensional problems.

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<table>
<thead>
<tr>
<th>Function</th>
<th>Statistic</th>
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</table>
4.3 Engineering problem

To augment the preceding evaluations the proposed method was also applied to an engineering problem of airfoil shape optimization to evaluate its effectiveness in a real-world problem. The goal is find an airfoil which maximizes its lift to drag ratio

\[ f = -\frac{c_L}{c_D} \quad (7) \]

where the latter are obtained from XFOil which is a numerical aerodynamic code for evaluation of subsonic airfoils [4]. Airfoils were represented with the NACA 4 digit system: % max camber (1 digit), % max camber (1 digit) x-position, %thickness (2 digits). Accordingly each airfoil was represented by a vector having 4 components. All other EA parameters were identical to the previous tests.

Table 4 gives the resultant test statistics from which it follows that the \( n=2, p=0.8 \) performed best closely followed by the \( n=2, p=0.4 \) variant. The baseline EA without the proposed method performed worse. Also, Figure 3 shows representative convergence plots of the three algorithms in the airfoil problem along with optimal airfoils obtained. In this example the 2nd variant with \( n=2 \) and \( p=0.8 \) achieved a lift to drag ratio of 242 while the 1st variant and the baseline algorithm achieved an airfoil with a ratio of 215, namely, a 12.5% improvement. The improved performance is attributed to the thinner airfoil shape which produces a lower drag.
Table 4: Benchmarking–Airfoil

<table>
<thead>
<tr>
<th>Statistic</th>
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<th>n=2,p=0.8</th>
<th>Baseline</th>
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<td>Max</td>
<td>−1.314e+02</td>
<td>−1.227e+02</td>
<td>−1.110e+02</td>
</tr>
</tbody>
</table>

Figure 3: Convergence plots for the airfoil problem.
5 Conclusion

Evolutionary algorithms have shown to be effective across a wide variety of optimization problems. However a main issue in their application is their often slow convergence speed and consequentially they require a large number of function evaluations. To address this issue this study has proposed a new method which accelerates their convergence by tracking the centroid of the EA population over several generations and then predicting the centroid in the next iteration. The EA population is then shifted in the direction of convergence without applying the evolutionary operators thereby reducing the computational load and accelerating convergence. Performance analysis based on a set of both low and high dimensional problems shows the effectiveness of the proposed method.

References


Research of Physical Alterations in Water Treated with Evodrop Turbine Technology

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Abstract
Experiments with Evodrop turbine treated water show alterations in its structuring in terms of a lower number of clusters and increased average number of molecules per cluster compared to control water, also corresponding to increased average energy of hydrogen bonds. Local maxima in the distribution of numbers of molecules with respect to energy were observed at -0.1112, -0.1212 and-0.1387 eV. The biggest stable clusters were observed at hydrogen bonds energy equal to...
- 0.1387 eV. They were modeled with dodecahedral structures consisting of 20 water molecules having a diameter of circumscribed spheres equal to 0.822 nm. Obtained values of pH and ORP showed closer similarity of Evodrop turbine water to neutral Catholyte in comparison with tap water.

**Keywords:** Evodrop turbine water, NES, DNES, number of water molecules, hydrogen bonds, clusters

1. **Introduction**

EVODROP water treatment technologies have been invented by Fabio Huether. It is based on ultra-nano membrane water filtration, turbine rotation treatment and electrochemical activation. Corresponding patents were filed with the Swiss Patent Office (IGE) on 04.03.2019 [1]. In addition, his partner Eng. Markus Wantscha and his PhD Advisory Board work on new methods and promote continuous improvement of these three different innovations. Our previous research has shown significant and favorable changes in water treated with EVODROP electrochemical activation [2]. The present work was dedicated to investigation of physical changes in water treated with Evodrop turbine Technology.

2. **Materials and Methods**

2.1. **Evodrop turbine water purifier**

The proprietary operating principle and developed geometry of Evodrop turbine (Fig. 1) allow for highly efficient treatment. Incoming water passes through rotating turbine, driving them with its pressure, whereby it passes through the device rotating at approx. 2,000 rpm. Specific outcomes of such treatment are based with and magnetohydrodynamic forces [3].

![Fig. 1. Evodrop turbine operation principle](image-url)
A water purifier comprising a nozzle (9) in a jacket tube (1). At least one inlet bore (21) connects an inlet-side section of the jacket tube (1) to a turbulence chamber (19) which is open in the direction toward an outlet-side section of the jacket tube (1). A water stream is deflected and swirled in the turbulence chamber (19) when flowing through the inlet bore (21). Subsequently, the rotating water stream passes the magnetic field of at least one magnet (11).

2.2. NES and DNES Spectral Analysis

NES and DNES spectral analysis was performed with an optical device invented by Antonov [4, 5]. Evaporation of water drops took place on a mylar foil pad supported by a glass plate in a hermetic chamber.

Its characteristics were:
1. Monochromatic light with wavelength \( \lambda = 580 \pm 7 \) nm (yellow color in the visible spectrum);
2. Angle of evaporation of water drops: from 72.3\(^0\) to 0\(^0\);
3. Temperature range: (+22–24 \(^0\)C);
4. Energy range of hydrogen bonds between water molecules: \( E = -0.08 \)–\(-0.1387 \) eV (corresponding to \( \lambda = 8.9 \)–13.8 \( \mu \)m of electromagnetic radiation).

2.3. Parameters of NES and DNES water spectra

The energy \( (E_{H_{2}O}) \) of hydrogen O...H-bonds between H\(_2\)O molecules in water samples was measured in eV. The function \( f(E) \) is called energy distribution spectrum. It was determined with the non-equilibrium process of water droplets evaporation. That is why the method is called Non-equilibrium energy spectrum (NES)[4, 5].

Figure 2 shows the schematics of the method for measurement of wetting angle of liquid drops on a hard surface.

![Fig. 2. Operation principle of the method for measurement of wetting angle of liquid drops on a hard surface: 1-drop, 2-thin maylar foil, 3-glass plate, 4-refraction ring width (a). The wetting angle \( \theta \) is a function of a and d3.](image-url)
The relation between \( f(\theta) \) and the energy of hydrogen bonds between water molecules is expressed as:

\[
f(E) = \frac{14.33 f(\theta)}{[1-(1+bE)^2]^2}
\]

where \( E \) is the energy measured in electron volts (eV) and the dimension of \( f(E) \) is \( \text{eV}^{-1} \).

In addition, the difference:

\[
\Delta f(E) = f(\text{sample}) - f(\text{control})
\]

is called Differential non-equilibrium energy spectrum (DNES) [4,5]. DNES is a measure of modification of water structure as a result of a certain varied experimental factor. The overall effect of all other uncontrolled factors is the same for the control and the sample. The dimension of DNES is \( \text{eV}^{-1} \).

### 2.4. Electrical Measurements

A HANNA Instruments HI221 meter equipped with Sensorex sensors was used for the measurement of Oxidation Reduction Potential (ORP) and pH. The range of HANNA Instruments HI221 meter is: pH - (2.00-16.00 ±0.01) And ORP (±699.9±0.01 – ±2000±0.1) mV

### 3. Results and Discussion

#### 3.1. Parameters of water molecules and hydrogen bonds

The water molecule has a size of 0.27 nm. Hydrogen bond length is 1.5-2.6 Å or 0.24-0.26 nm [6]. The covalent bond length is 0.096 nm. Hydrogen bond strength between two water molecules is 5-6 kcal/mol or 0.22-0.26 eV [7].

In spectral analyses using NES and DNES methods the range of research is (-0.0912)-(-0.1387) eV. For energy among the electromagnetic hydrogen bonds of (-0.0912) eV evaporates the top layer of water drops. For energy among the electromagnetic hydrogen bonds of (-0.1387) eV evaporate the last water molecules [8].

We adopt Saykally’s model according to which the total number of available hydrogen bonds is maximum for 100 water molecules (Fig. 3) [9, 10].
Fig. 3. Saykally’s model of total available hydrogen bond numbers

Table 1 and Fig. 4 show the distribution of numbers of water molecules according to the energy of hydrogen bonds per each 100 water molecules in the bulk volume of Evodrop turbine and control water.

Table 1: Distribution of numbers of water molecules according to the energy of hydrogen bonds per each 100 water molecules in the bulk volume of Evodrop turbine water

<table>
<thead>
<tr>
<th>-E[eV]</th>
<th>Evodrop turbine Water</th>
<th>Control Water</th>
<th>-E[eV]</th>
<th>Evodrop turbine Water</th>
<th>Control Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0912</td>
<td>0</td>
<td>8</td>
<td>0.1162</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.0937</td>
<td>0</td>
<td>0</td>
<td>0.1187</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>0.0962</td>
<td>5</td>
<td>8</td>
<td>0.1212</td>
<td>15</td>
<td>4</td>
</tr>
<tr>
<td>0.0987</td>
<td>4</td>
<td>0</td>
<td>0.1237</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>0.1012</td>
<td>0</td>
<td>8</td>
<td>0.1262</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.1037</td>
<td>0</td>
<td>6</td>
<td>0.1287</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>0.1062</td>
<td>10</td>
<td>8</td>
<td>0.1312</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>0.1087</td>
<td>0</td>
<td>8</td>
<td>0.1337</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>0.1112</td>
<td>12</td>
<td>0</td>
<td>0.1362</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>0.1137</td>
<td>0</td>
<td>5</td>
<td>0.1387</td>
<td>18</td>
<td>7</td>
</tr>
</tbody>
</table>
These distributions are basically connected with spatial arrangement of \( \text{H}_2\text{O} \) molecules with equal energies of hydrogen bonds. This is a useful mathematical model for explaining the behavior of Evodrop turbine water, also describing structuring of \( \text{H}_2\text{O} \) molecules in clusters [11, 12].

In particular, at hydrogen bonds energy \( E = -0.1387 \text{ eV} \) in Evodrop turbine water, we have estimated that the biggest stable clusters can consist of 18 water molecules. Their hydrogen bonds are measured last during evaporation of water according to the wetting angle. Such preliminary considerations lead to a realistic model of stable clusters with 20 water molecules arranged in dodecahedral structures shown in Fig. 5. Their size can be estimated using the diameter of circumscribed spheres, provided that nuclei of oxygen atoms are located at dodecahedron vertices [13,14].

**Figure 4.** Graphic representation of the numbers of water molecules at different measured values of hydrogen bonds energy per each 100 water molecules in the bulk volume of Evodrop turbine (red line) and control water (green line).

**Fig. 5.** Dodecahedral cluster structure with 20 water molecules and the diameter of its circumscribed sphere.
Observed local maxima at -0.1112, -0.1212 and -0.1387 eV are in line with previous results published by Antonov, Ignatov and al. [4, 5, 11, 12]. According to Antonov and Galabova, -0.1112 eV hydrogen bonds energy is related to stimulating effects on the nerve system and nerve conductivity with calcium ions [3, 4]. In addition, according to Ignatov, -0.1212 eV is related to anti-inflammatory effects [15] and Antonov has shown that -0.1387 eV is related to inhibition of tumor cells development on molecular level [3]. That is why, similar favorable health effects could be expected from Evodrop turbine water.

3.2. pH and ORP measurements, Number of clusters, Average Number of Molecules per Cluster and Average energy of Hydrogen Bonds

Measured values of pH and ORP [16, 17] as well as derived values of cluster numbers and average energy of hydrogen bonds for Evodrop turbine and control water are shown in Table 2.

Average energy \(-E\) of hydrogen bonds was calculated as [14]:

\[
< -E > = \sum_{i=1}^{n} n_i E_i
\]

where \(n\) is the total number of molecules according to the adopted model, \(k\) is the number of clusters, \(n_i\) is the number of molecules in the \(i\)-th cluster, and \(E_i\) is the energy of hydrogen bonds corresponding to the \(i\)-th cluster.

**Table 2.** Values of pH, ORP, number of clusters per 100 molecules and average energy of hydrogen bonds for Evodrop turbine and control water.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Evodrop turbine</th>
<th>Control</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>6.54</td>
<td>7.78</td>
<td>-1.24</td>
</tr>
<tr>
<td>ORP [mV]</td>
<td>80</td>
<td>320</td>
<td>-240</td>
</tr>
<tr>
<td>Number of clusters per each 100 water molecules</td>
<td>10</td>
<td>14</td>
<td>-4</td>
</tr>
<tr>
<td>Average number of molecules per cluster</td>
<td>10</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Average energy (&lt;E&gt;) [eV]</td>
<td>-0.1219</td>
<td>-0.1123</td>
<td>-0.0096</td>
</tr>
</tbody>
</table>
Decreased pH value of Evodrop turbine water points to increased number of hydrogen ions, i.e. to possibility of more hydrogen bonds. In such a case, the number of clusters will be decreased and the average number of molecules per cluster will be increased compared to control water. All this will result in increased average energy of hydrogen bonds as shown in the above table. Decreased value of ORP points to increased number of electrons which enhances the antioxidant ability of Evodrop turbine water.

4. Conclusion

Evodrop turbine technology is capable of inducing significant physical changes in treated tap water, without external power supply. Their overall consideration points to possible favorable health effects of its everyday use as drinking water.

References


Tests on Fuel Cell by Innovative Small Size Prototype Plant

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Abstract

The company noted that hospitals need continuous energy throughout the year, also using cogenerates powered by fossil energy sources (methane, diesel, LPG, etc.). The Company, evaluating the possible alternative energy solutions to the traditional, highly polluting ones, has carried out a careful technical-scientific analysis, also thanks to the internal staff, on technologies that are partially mature but which, to date, find applications difficult for high costs and/or due to lack of technical-scientific knowledge. From here, the Company evaluated the application of Fuel Cells in the healthcare sector with the possibility of converting current cogenerates powered by fossil sources with hydrogen-powered fuel cells. This would also make it possible to guarantee alternative sources of supply, allowing, in the event of emergencies, to have energy sources capable of making the health structures autonomous.

Keywords: MCFC, Fuel Cells, prototype small-size, tests, dissemination

1. Introduction

The fuel cell is an electrochemical system capable of converting the chemical energy of a fuel directly into electrical energy, without the intermediate intervention of a thermal cycle, thus obtaining higher conversion efficiency than those of thermal machines conventional. The birth of fuel cells dates back to 1839, the year in which the English William Grove reported the results of an experiment in which he was able to generate electricity in a cell containing sulfuric acid, where two electrodes, consisting of thin sheets of platinum, on which hydrogen
and oxygen respectively arrived. A fuel cell works in a similar way to a battery, as it produces electrical energy through an electrochemical process; however, unlike the latter, it consumes substances from the outside and is therefore able to function without interruption, as long as the system is supplied with fuel (hydrogen) and oxidizer (oxygen or air).

The cell is composed of two electrodes in porous material, separated by an electrolyte. The electrodes act as catalytic sites for cell reactions that basically consume hydrogen and oxygen, producing water and passing electric current in the external circuit. The electrolyte has the function of conducting the ions produced by one reaction and consumed by the other, closing the electrical circuit inside the cell, and at the same time preventing mixing between anode and cathode gases. The final reaction that takes place inside the cell is exergonic, that is, it occurs by releasing energy; this manifests itself in the form of heat and electricity.

2. Materials and Methods

Prototype developed.

The prototype system is made up of a fuel processing unit and a power unit characterized by two MCFC fuel cell stacks. The hydrogen produced is developed by a hydrolyzer that separates H$_2$ and O$_2$ from distilled water (Figure 1).
The system was modified, changing the polymer fuel cell with a molten carbonate one, as the goal was to evaluate the performance of this cell for study purposes and for a potential application in the reference sector. In Figure 2, we can see how the replacement took place.

Once the system was defined, several tests were carried out with different loads, evaluating the efficiency of the molten carbonate fuel cell on a scale. The first test is shown in the diagram below in Table 1:

<table>
<thead>
<tr>
<th>R Ω</th>
<th>t [s]</th>
<th>Vol1 cm³</th>
<th>Volts [V]</th>
<th>I = mA</th>
<th>H₂consumato cm³</th>
<th>η (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>180</td>
<td>6,5</td>
<td>0,74</td>
<td>233</td>
<td>5,2</td>
<td>93</td>
</tr>
<tr>
<td>5</td>
<td>200</td>
<td>5,5</td>
<td>0,65</td>
<td>220</td>
<td>5,5</td>
<td>85</td>
</tr>
<tr>
<td>10</td>
<td>250</td>
<td>4,5</td>
<td>0,55</td>
<td>215</td>
<td>6,7</td>
<td>75</td>
</tr>
<tr>
<td>50</td>
<td>300</td>
<td>3,5</td>
<td>0,45</td>
<td>200</td>
<td>7,5</td>
<td>70</td>
</tr>
<tr>
<td>100</td>
<td>350</td>
<td>2,5</td>
<td>0,30</td>
<td>150</td>
<td>6,5</td>
<td>65</td>
</tr>
<tr>
<td>200</td>
<td>400</td>
<td>2,0</td>
<td>0,25</td>
<td>100</td>
<td>5,0</td>
<td>55</td>
</tr>
</tbody>
</table>

Table 1. Test in lab on the prototype
3. Results and Discussion

Faraday efficiency is the ratio of the theoretical volume of hydrogen consumed by the load at a certain current flow and the experimentally determined consumption of hydrogen.

- $\eta = \text{Vol H}_2$ - Faraday efficiency should be 1 (100%).
- $\text{H}_2 \rightarrow 2\text{H} + + 2e^-$, so 1 mole of hydrogen gas gives 2 moles of electrons.
- A mole of electrons has a charge equal to 96,500 C.
- So 24,000 cm$^3$ H$_2$ gives (2 $\cdot$ 96,500 C) = 193,000 C.

In this experiment, the fuel cell supplies 233 mA (= 0.233 A) for 180 s. Therefore the theoretical volume of the hydrogen consumption is:

- $\text{Vol H}_2 = (0.233A \cdot 180s \cdot 24.000 \text{ cm}^3) / (193.000 \text{ C})$
- $\text{Vol H}_2 = 5.2 \text{ cm}^3$

Therefore the efficiency is:

$\eta = \text{Vol H}_2 \text{ (th.)} / \text{Vol H}_2$

$\eta = 5.2 \text{ cm}^3 / 5.6 \text{ cm}^3$

$\eta = 0.93$ (93%).

The cell efficiency trend as a function of the load variation and indirectly of the variables listed above, of the tests carried out, are correlated in the following graphs.
4. Conclusion

The purpose of the work carried out was precisely to investigate a sector that presents a very high possibility of expansion, in fact the characteristics of great flexibility in the use of fuels and high yields, independent of the nominal power of the modules used and the size of the plant, make it possible to install fuel cells even in small plants

References


Optimizing the Performance of the Wort Preheater with the Aim of Improving Resource Efficiency in Beer Production

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Abstract

Resource efficiency in the brewing industry involves the use of energy and water with minimal wastage and negative environmental impact. As it is often impossible to maintain the recommended parameter values in the actual operation of the plant, due to a number of disturbance factors, it is necessary to find an easy and efficient way to maintain the parameter values in the relationships that result in the least possible losses. This paper presents the use of a software simulation model for the purpose of simulating the operation of a wort preheater, with the aim of managing its operation in a real environment with maximum resource efficiency.

Keywords: resource efficiency, brewing industry, wort preheater

1 Introduction

Resource efficiency in production has arisen as one of the main requirements to achieve in modern industrial sites [1]. It represents a way to make better use of the resources used in a particular technology/production process. With the above goal
in mind, there exist a bunch of approaches to quantify the performance of a production process like, for instance, the very extended one called Key Performance Indicators (KPI) [2]. These indicators are usually computed for long-time periods like months or after the production campaign is finished. So, they are not suitable to support operational decisions. This need has led to the recently developed set of the so-called Resource Efficiency Indicators (REI) [3]. The aim of these indicators is computing resource-efficiency measurements in short periods of time (even online), so they can be used for decision support to improve process operation in real time. [4]. In this paper, we aim to address the problem of resource efficiency in beer production, particularly efficiency of wort preheater. By using an offline simulation model to predict performance of the preheater in various cases, it is possible to gather data which can later be use for calculation of Resource Efficiency Indicators.

Also, efficient use of resources means minimization of potential pollution "at source", it is possible to suppress excessive pollution of natural resources: water, land and air. Therefore, resource efficiency represents a preventive action which is aimed to maximize the use of limited resources and minimize losses (waste, waste streams). Industrial plants are significant pollutants, which is also the case with beer production considered in this paper. Beer production is a significant consumer of various types of resources, the most important being water, heat and electricity. High water consumption is characteristic of this type of industry due to the high requirements for compliance with hygiene standards. Water is used in beer production for technological, energy and sanitation purposes. It is primarily used as a raw material but also for other production and non-production processes in the brewing industry. Thermal energy is used in production departments with the highest consumption in the boiling plant, but it is also used in other parts of the technological process of production, as well as in non-production segments within the entire plant.

The ways of optimizing the use of water and boiler fuel in the production of industrial steam can be collectively referred to as resource efficiency. Appropriate measures, based on constant monitoring of energy and production flows, can achieve energy savings of 10-15%. The main resources in the production of industrial steam are water and energy, which should be used efficiently. In doing so, it is necessary to ensure sufficient quantities of quality water, which is possible by applying a developed technological process that involves the preparation, maintenance and control of water quality in all segments of the water-steam cycle [5]. Systems for steam distribution and condensate recovery, together with the boiler room and final consumers, represent a system for centralized energy supply as a heat carrier. The return of the condensate from the process to the boiler room and its reuse means energy Brewery water consumption ranges from 0.32-2.0 [m³/hl of beer], thermal energy consumption ranges from 118.7-355 [MJ/hl of beer], while electricity consumption ranges from 7-12.5 [kWh/hl of beer] [6]. Consumption of certain types of energy and water in the production of beer depends on a number of factors, and therefore the above specific consumption intervals are quite wide. Accordingly, the assessment of the justification of current
energy consumption should be made at each facility [6].

2 Beer production technology

The data presented in this paper are for the Tuzla Brewery, Bosnia and Herzegovina. The Tuzla Brewery has been operating continuously since 1884, producing beer, mineral water and juices. Cooling energy consumption occurs in all key beer production processes. Technologists are constantly monitoring energy consumption and trying to reduce it per unit of product. With the measures taken, electricity consumption for the operation of ammonia refrigeration compressors can be reduced by up to 13% [7]. Energy efficiency is an important component of the plant in its environmental strategy. Electricity and heat are used in the brewing process. Thermal energy is used to produce steam in boilers, which is mainly used for boiling wort and heating water [8]. The beer industry is usually a high pollution and energy consumption industry and the polluter has a huge environmental impact. Therefore, it is necessary to reduce energy consumption and emissions in the brewing industry [9,10]. Cleaner production means production processes, the conservation of raw materials and energy, maximizing waste reduction, recycling and reuse at the enterprise level, as well as reducing the amount and toxicity of all emissions and waste before they exit the production process [9].

Any improvement in the steam distribution and condensate recovery systems has a direct effect on the heat transfer to end users and on the efficiency of the boiler and associated equipment [11]. Resource efficiency in the production of industrial steam is affected by: quality of boiler feed water, type and cycle of boiling and desalination of boilers, condensate recovery from the process, oxygen content \( \text{O}_2 \) in flue gases, flue gas temperature, fuel temperature at the inlet to the burner, pipe insulation, valves, flanges, chimneys and other boiler equipment, etc. [11,12,13,14].

Beer production is the central plant of the factory, and includes several stages, whereas regarding consumption of resources (water and heat), the boiling plant stands out, the scheme of which is given in Figure 1. Figure 1 shows the scheme of part of the production process in the boiling plant. Attention should be paid to the heat exchangers i.e wort preheater and wort cooler, since their operation directly affects the efficient consumption of resources (energy and water). The technological process of beer production should be performed according to the standardized values of pressure, temperature and flow at appropriate points in the production cycle, in which case the best use of resources is achieved. However, in actual work, it often happens that individual parameters deviate from the normalized values. The causes of deviations are different, leading to resource losses and the need to optimize parameters to improve resource efficiency. Care should be taken that optimization of the parameters should not impair the technological process of beer production. In accordance with the above, the values of the wort and water parameters at the inlet and outlet of the preheater and cooler standardized. However, if one of them deviates other parameters should be adjusted in order to maintain maximum energy and resource.
efficiency of the mentioned heat exchangers. Figure 2 shows a wort preheater, whose resource efficiency will be analyzed below.

![Figure 1 Scheme of the production process in the boiling plant](image)

A simulation model was installed for the selected preheater in order to determine, to which extent and how, the deviations of the parameters of the heat transmitter and receiver (water and wort) affect the efficient use of energy and water in the production process. Based on the results of simulations of the preheater operation, the optimal values of water and wort parameters in the actual operation could be determined, in order for the exchanger to operate with maximum energy resource efficiency.

![Figure 2 Wort preheater in Tuzla Brewery](image)

There are normative setpoints for the parameters of the heat transmitter and receiver entering the preheater, as well as the deviation intervals that are "allowed" by these same standards. It has been demonstrated by experience that deviations from the norms within the recommended limits do not affect the technological process of production, but it is proved that any significant deviation
of parameters from normative setpoints causes a decrease in the overall degree of efficiency of the plant. Due to all of the above, the simulation model for the selected exchanger was set up.

3 A simulation performance model of the wort preheater

GateCycle™ software, is used to model the preheater performance. This software can be used for both design and performance evaluation of elements of thermal power plants. GateCycle™ is a combination of a graphical user interface with detailed analytical models of thermodynamic processes in thermal power plants, as well as heat transfer and flow processes, which enables design and simulation analyzes of all levels of complexity, some of which are:

- Performance simulations of system elements for “off design” working conditions, when main design characteristics have already been set and cannot be changed (i.e. heat exchange surface of a preheater);
- Predicting the effects of proposed parameter changes on existing plant elements (i.e changing one or more operating parameters of a heat transmitter/receiver to achieve maximum resource efficiency of the heat exchanger, if for some reason one or more parameters deviate from their nominal values thereby exchanging the heat with reduced utilization);

The software model was created and verified using data from normative testing conducted for Tuzla Brewery. In case of preheater operation at the normative values of the above parameters, the heat received by the wort is calculated using the expression (1):

\[
Q_s = 125 \cdot 1045 \cdot 3.98 \cdot (95 - 72) = 3321.5[kW]
\]

while the amount of heat delivered by the water is (2):

\[
Q_l = 155 \cdot 1000 \cdot 4.187 \cdot (97 - 78) = 3425.2[kW]
\]

In the ideal case of heat transfer, the values defined by expressions (1) and (2) would be equal. In the case of realistic operating conditions, this difference is due to heat transfer losses. The degree of utilization of the exchanger is greatest when the parameters are equal to nominal, as shown by expressions (1) and (2). The quantities of heat delivered and received are determined by the expression (3):

\[
Q = m \cdot \rho \cdot c_p \cdot (t_{ul} - t_{ol})
\]

where are: \(Q\) - amount of heat exchanged (transmitted from water to wort) [kW], \(c_p\) - specific heat capacity (water/wort) [kJ/kgK], \(\rho\) - density (water/wort) [kg/m³], \(m\) - flow (water/wort) [m³/h], \(t_{ul}\) - outlet temperature (water/wort) [°C], \(t_{ol}\) - inlet temperature (water/wort) [°C].
Figure 3 (L), shows a design model of a preheater and simulation model convergence, containing elements that define heat exchanger, as well as water and wort inlet/outlet parameters. Adjustment of the data in the project model was carried out until satisfactory agreement of data from the project model and normative tests was achieved. The stacking was related to the size of the heat exchange surface, the inlet/outlet water/wort temperatures, the water/wort flow as well as the convection heat transfer coefficient. Recommendations from the literature and practice state that the values of the convection heat transfer coefficients range from $\alpha = 2,000\text{ to }4,000 \text{ [W/m}^2\text{K}]$ [15], where the following operating conditions apply: for poor conditions $\alpha = 400 \text{ [W/m}^2\text{K}]$, for normal conditions $\alpha = 1,600 \text{ [W/m}^2\text{K}]$, for good conditions $\alpha = 7,000 \text{ [W/m}^2\text{K}]$.

When fitting the model, the value of the convection heat transfer coefficient for normal to good conditions was adopted, taking into account the operating conditions of the heat exchanger, which include soiling, limescale etc. By comparing the values of the parameters obtained for the design model with the values of the same parameters from the normative tests, it was found that there is a mean relative deviation of up to 5%, which is satisfactory in this case.

Verification and validation of the model was carried out, as well as its "locking" and switching to "off-design" mode, a simulation version in which it is not possible to change the value of the exchange surface or the convection heat transfer coefficient. However, in the simulation version of the model, it is possible to change the values of the input parameters such as temperature and water/wort flow, and monitor the resulting water/wort temperature output values accordingly. Although the simulation model is validated with respect to the design parameters, in order to be considered useful, it is necessary to converge the simulation model after an iterative simulation process when changing any of the input parameters (temperature, water/wort flow at the inlet to the exchanger) in order for the output values of the parameters to be obtained. Figure 3 (R), shows a convergence of the simulation model.
4 Analysis of simulation results

During the actual operation of the plant, due to various disturbance factors, it is impossible to constantly maintain exactly the set values of the input parameters in the preheater, equal to the nominal values from the normative tests. Therefore, based on work experience, it is recommended that temperatures be maintained within the recommended limits. The water entering the preheater of the wort to heat it should have a temperature in the range $t_{in} = 90-98 \, ^{\circ}{\text{C}}$. According to the norm, the wort flow rate is $36.28 \, [\text{kg/s}]$ and has not been changed during the simulations. During the actual process, it is not recommended to change this parameter due to the technological process of beer production. The water at the outlet of the preheater is cooled and is recommended to be in the range of 75-85 $[^{\circ}{\text{C}}]$. From the preheater, the water goes to an energy tank where it is reheated. The output temperature of the wort should be in the range $t_{out} = 90-99 \, [^{\circ}{\text{C}}]$, where it is recommended to keep this temperature closer to the upper limit due to the process subsequently taking place in the wort boiler. In compliance with the quality of the beer production process, the temperature of the wort at the inlet of the preheater should be in the range of 72-75 $[^{\circ}{\text{C}}]$. Considering the recommended interval limits for water and wort temperatures, and changing the water flow but not the wort flow, eight series of simulations were performed for different combinations of the above parameters. From eight series of simulations i.e. dozens of individual simulations that satisfy from the point of view of the convergence of the simulation model, only those were originally singled out that were found to match the output results with the aforementioned parameter intervals. This satisfied the practice recommendation and rejected all other simulations as unsatisfactory. Following the recommended intervals for the output parameters, over 50 valid simulations were obtained. For these, the absolute and relative error deviations were calculated by comparing simulation obtained value of the exchanged amount of heat between water and the wort, and its nominal value which is $3321.5 \, [\text{kW}]$. Relative errors were in the range of 0.5-25% , indicating that in the actual operation of the plant situations can occur when there is a significant deviation of the actual efficiency of the heat exchanger from its nominal value, resulting in the loss of resources. Then, from the set of valid simulations, those for which the value of the relative error in the heat exchange is greater than 5% were excluded, and the results of remaining simulations are shown in Table 1 (below). The reason for choosing only these simulations lies in the assumption that in the given situations, in case of change of one of the input parameters, it would be easier and faster to correct another parameter in order to "iron out" the difference in deviation of the actual from the nominal operating conditions. In accordance with the foregoing, Table 1 shows the results of simulations of the work of the wort preheater, in cases where the water and wort temperatures are at the recommended intervals, although still deviating from the recommended normative value. The resulting simulation values of the heat exchanged between heat transmitter (water) and the heat receiver (wort) are also shown.
Table 1 Results of series of simulations that comply with pre-conditions for water/wort temperatures and flow

<table>
<thead>
<tr>
<th>No.</th>
<th>$t_{\text{w}in}$ (°C)</th>
<th>$t_{\text{w}out}$ (°C)</th>
<th>$m_w$ (kg/s)</th>
<th>$t_{\text{i}w}$ (°C)</th>
<th>$Q_{\text{sim}}$ (kW)</th>
<th>$\Delta Q$ (kW)</th>
<th>$\Sigma Q = \frac{\Delta Q}{Q_{\text{norm}}}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>97</td>
<td>77,86</td>
<td>43.05</td>
<td>94.51</td>
<td>3250.7</td>
<td>70.76</td>
<td>2.13</td>
</tr>
<tr>
<td>2.</td>
<td>98</td>
<td>78.09</td>
<td>43.05</td>
<td>95.41</td>
<td>3380.7</td>
<td>59.21</td>
<td>1.78</td>
</tr>
<tr>
<td>3.</td>
<td>97</td>
<td>77.30</td>
<td>41</td>
<td>94.06</td>
<td>3185.7</td>
<td>135.75</td>
<td>4.08</td>
</tr>
<tr>
<td>4.</td>
<td>97</td>
<td>77.57</td>
<td>42</td>
<td>94.28</td>
<td>3217.5</td>
<td>103.98</td>
<td>3.13</td>
</tr>
<tr>
<td>5.</td>
<td>97</td>
<td>77.85</td>
<td>43</td>
<td>94.5</td>
<td>3249.2</td>
<td>72.21</td>
<td>2.17</td>
</tr>
<tr>
<td>6.</td>
<td>97</td>
<td>78.12</td>
<td>44</td>
<td>94.69</td>
<td>3276.7</td>
<td>44.77</td>
<td>1.35</td>
</tr>
<tr>
<td>7.</td>
<td>97</td>
<td>78.39</td>
<td>45</td>
<td>94.88</td>
<td>3304.1</td>
<td>17.33</td>
<td>0.52</td>
</tr>
<tr>
<td>8.</td>
<td>98</td>
<td>76.68</td>
<td>38</td>
<td>94.13</td>
<td>3195.8</td>
<td>125.64</td>
<td>3.78</td>
</tr>
<tr>
<td>9.</td>
<td>97</td>
<td>77.86</td>
<td>43.05</td>
<td>94.51</td>
<td>3250.7</td>
<td>70.76</td>
<td>2.13</td>
</tr>
<tr>
<td>11.</td>
<td>97</td>
<td>77.86</td>
<td>43.05</td>
<td>94.51</td>
<td>3250.7</td>
<td>70.76</td>
<td>2.13</td>
</tr>
<tr>
<td>12.</td>
<td>97</td>
<td>77.86</td>
<td>43</td>
<td>94.51</td>
<td>3250.7</td>
<td>70.76</td>
<td>2.13</td>
</tr>
<tr>
<td>13.</td>
<td>96,5</td>
<td>77.99</td>
<td>44</td>
<td>94.24</td>
<td>3211.7</td>
<td>109.75</td>
<td>3.30</td>
</tr>
<tr>
<td>14.</td>
<td>96</td>
<td>78.44</td>
<td>45</td>
<td>93.87</td>
<td>3158.3</td>
<td>163.18</td>
<td>4.91</td>
</tr>
<tr>
<td>15.</td>
<td>97</td>
<td>77.85</td>
<td>43</td>
<td>94.5</td>
<td>3249.2</td>
<td>72.21</td>
<td>2.17</td>
</tr>
<tr>
<td>16.</td>
<td>96,5</td>
<td>77.99</td>
<td>44</td>
<td>94.24</td>
<td>3211.7</td>
<td>109.75</td>
<td>3.30</td>
</tr>
<tr>
<td>17.</td>
<td>96</td>
<td>78.13</td>
<td>45</td>
<td>93.96</td>
<td>3171.3</td>
<td>150.19</td>
<td>4.52</td>
</tr>
</tbody>
</table>

By comparing the simulation and the normative value of the exchanged amount of heat, the simulation values are lower in absolute terms. If only the absolute difference of the changed quantities of heat were observed, the conclusion would be that the heat exchange in the preheater is realized with less specific energy consumption. However, such savings are apparent because they are mainly due to the lower output temperature of the wort, and accordingly it will be necessary to bring more energy into the wort boiler. Table 1 also shows the relative deviations of the exchanged amount of heat according to the simulations and the norm i.e. with a relative error of less than 5%. The simulations shown can serve to control the production process in a facility. In case of deviation of the input parameters of water or wort in the preheater, it may be decided to adjust one or more parameters (i.e. flow or temperature of the inlet water) to bring the process as close as possible to the normative values and thus avoid unnecessary waste of resources. Of course, it is impossible to predict all possible combinations of parameters that can occur in a real process, but it is possible to find a more approximate combination of parameters that causes the least possible loss of resources. As mentioned above, if the simulation results are used to manage the current parameters as the process proceeds, it is recommended to select those simulations that have a smaller relative deviation of the exchanged amount of heat compared to the normative one. The amount of the maximum allowable relative deviation
can be estimated on the basis of previous experience, where it should not exceed the 10% limit.

5 Conclusion

Resource efficiency in the production process is significant, both from the point of view of optimal use of resources and because of the need for minimal negative environmental impact. Given that operating parameters in the production process often deviate from their prescribed values and thus lead to inefficient use of resources, there is a need to resolve such situations on the spot and preferably in a simple and efficient manner. This paper shows how the use of a simulation computer model, which is based on a mathematical model of heat exchange in a wort preheater, can adjust the appropriate input parameters in response to the deviation of other input parameters as well. The ultimate goal is to achieve a minimum deviation of efficiency from its normative value, that is, maximum resource efficiency.

References


The Influence of the Radiation Frequency on the Duration of the Sintering Process of Metal Powders

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Abstract

This paper demonstrates the advantage of using sintering technology based on the effect of atomic electron interaction. This effect occurs as a result of the simultaneous exposure to an electromagnetic field of the petahertz frequency range and a constant magnetic field. This leads to a significant reduction in the duration of pore overgrowth and, accordingly, the duration of the sintering process. The tasks that have been done in this study is to prove that the described method is a more effective and promising sintering method compared to classical sintering in muffle furnaces. The obtained results show that using sintering technology based on the effect of atomic electron interaction allows to reduce the sintering time by several times in comparison with traditional sintering technology.

Keywords: anomalous penetration, sintering, thermal diffusion, Lorentz force, pore overgrowth

1. Introduction

Recent decades have been marked by an active study of such a field of science and technology as powder metallurgy [1-3]. The search for a method of accelerating the sintering process of metal powder materials is of particular interest to researchers in this field. The solution to this problem is to study the behavior of electrically conductive materials when exposed to electromagnetic radiation of different frequency ranges. Increasing the frequency of electromagnetic heating to the ultraviolet range with the simultaneous presence of a constant magnetic field leads to the effect of the so-called anomalous penetration of moving free electrons from the metal surface into the depth of the sintered billet [4]. A number of studies have
demonstrated that a metal in a constant magnetic field can be transparent to electromagnetic radiation, and in some cases generally behaves like a dielectric. On the one hand, temperature additives appear in a metal due to quantum energy transitions, and, on the other hand, electron flows, penetrating into crystalline structures, create the force of pressure of the electron flow on the atoms of the substance. Atoms move from the boundaries of crystals into the voids of matter, where the bulk of free vacancies are located.

This paper describes the theoretical background of the method of accelerating mass transfer during sintering of metallic substances (for example, powdered iron) due to the appearance of additional driving forces of the influence of electromagnetic fields on the diffusion of atomic particles. A mathematical comparative analysis of the duration of complete overgrowth of the pores is carried out in the case of using the described method and using the traditional and most common technology of sintering of powdered metal materials - sintering in a muffle furnace [5].

2. Driving forces of diffusion

The main flows of diffusing particles during sintering are associated with the concentration gradient of vacancies at the “powder” - pore boundaries and thermal gradient in the volume of the sintered product (thermal diffusion) [6; 7]. The equation for the total diffusion flux has the form of equation (1), in which the first component relates to thermal diffusion \( J_T \), the second to the vacancy concentration gradient \( J_L \):

\[
\sum J = J_T + J_L = -D \cdot n \cdot \left( \frac{Q_T \cdot \nabla T}{kT^2} + \frac{8\pi\alpha}{kT \cdot S} \right)
\]  

in which \( T \) is the heating temperature, \( \alpha \) is the surface energy at the border “powder – pore”, \( S \) is the area of the spherical surface of the pore, \( Q_T \) is the heat of transfer of atomic particles (for ionic compounds \( Q_T \approx 1 \) eV), \( \nabla T \) is the temperature gradient in sintered billet volume.

By determining the magnitude of the microparticle flow, we can calculate the duration of pore overgrowth.

\[
t_p = \frac{N_p}{\sum J \cdot S_p} \text{ [c]},
\]

here \( S_p \) is the surface area of the pore, \( N_p \) is the required number of atoms to fill the pore with a diameter \( d_p \cdot N_p = 4\pi \cdot d_p^3 / (3 \cdot a) \), where \( a \) is the interatomic distance.
Below (Table 1), calculations of the time of pores overgrowth of powdered iron of different dispersion (pore radius 3 μm, 7.217 μm and 10 μm) at heating temperatures (1373K - 1573K) in case of sintering in a muffle furnace are presented. The calculations were performed according to the formula (1).

The diffusion coefficient was determined by the formula:

\[ D = D_0 \cdot e^{\frac{E_a}{RT}}, \]  

(3)

where \( D_0 = 2 \cdot 10^{-4} \) m²/c is the preexponential factor [8], \( E_a = 250000 \) kJ/mol [8] is the diffusion activation energy for iron (α-Fe), \( R \) is the universal gas constant.

<table>
<thead>
<tr>
<th>Pore radius, ( r ) (μm)</th>
<th>Diffusion coefficient, ( D ) (m²/c)</th>
<th>Temperature, ( T ) (K)</th>
<th>Total flow, ( \sum J = J_T + J_L ) [1/ (m²/c)]</th>
<th>Duration of pore overgrowth, ( t_p ) (c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.217</td>
<td>1.12 \cdot 10^{-12}</td>
<td>1573</td>
<td>3.05 \cdot 10^{18}</td>
<td>12600 (3.5hr)</td>
</tr>
<tr>
<td></td>
<td>1.5 \cdot 10^{-13}</td>
<td>1473</td>
<td>4.43 \cdot 10^{17}</td>
<td>82200 (23hr)</td>
</tr>
<tr>
<td></td>
<td>0.56 \cdot 10^{-13}</td>
<td>1373</td>
<td>1.83 \cdot 10^{17}</td>
<td>200000 (56hr)</td>
</tr>
<tr>
<td>10</td>
<td>1.12 \cdot 10^{-12}</td>
<td>1573</td>
<td>2.09 \cdot 10^{18}</td>
<td>24151 (7hr)</td>
</tr>
<tr>
<td></td>
<td>1.5 \cdot 10^{-13}</td>
<td>1473</td>
<td>3.07 \cdot 10^{17}</td>
<td>164420 (46hr)</td>
</tr>
<tr>
<td></td>
<td>0.56 \cdot 10^{-13}</td>
<td>1373</td>
<td>1.29 \cdot 10^{17}</td>
<td>391300 (108hr)</td>
</tr>
<tr>
<td>3</td>
<td>1.12 \cdot 10^{-12}</td>
<td>1573</td>
<td>12.61 \cdot 10^{18}</td>
<td>1201 (0.4hr)</td>
</tr>
<tr>
<td></td>
<td>1.5 \cdot 10^{-13}</td>
<td>1473</td>
<td>17.96 \cdot 10^{17}</td>
<td>8435 (2.5hr)</td>
</tr>
<tr>
<td></td>
<td>0.56 \cdot 10^{-13}</td>
<td>1373</td>
<td>7.23 \cdot 10^{17}</td>
<td>20954 (6hr)</td>
</tr>
</tbody>
</table>

Table 1: The calculation results of the duration of pore overgrowing at different values of the pore radius and heating temperature.
Based on the above table and graph, it can be concluded that the smaller the pore size and the higher the heating temperature, the faster the powder pore disappears.

3. Atomic – electron interaction

Next, we proceed to consider the method proposed by the author. The idea is to increase the frequency of electromagnetic radiation to $\nu = 10^{14} - 10^{15}$ Hz in the presence of a constant magnetic field (magnetic induction $B \geq 0.5$ T). Comparing this frequency value and the radiation frequency in the case of heating in a muffle furnace ($\nu = 10^{11} - 10^{14}$ Hz), we can notice a difference of several orders of magnitude. The combination of these two fields leads to the effect of anomalous penetration (AP) of moving free electrons from the metal surface into the depth of the sintered billet. This leads to an additional driving force called electron “wind” [9] or electric transport. In this paper, this effect is called "atomic - electron interaction" and is designated as $J_{A,E}$.

Finding a value $J_{A,E}$ is possible by considering the physics of the process of high-frequency energy transfer using this heating method.

Free electrons, having absorbed quanta of the electromagnetic field, move to a greater depth of the sintered powder material. As a result of scattering on defects and impurity atoms, electron fluxes transfer their kinetic energy to the atoms of the crystal lattice, pushing them to move into free vacancies [10], the bulk of which are located in the pores between the powders.
An atom, having received an energy impulse, begins to diffuse into the free pores of the substance. By analogy with Newton's second law [11], the atom will be affected by force $F_a$:

$$F_a = C_F \cdot m_e \cdot S \cdot v^2 \ [N].$$

Here $F_a$ - energy impulse received by the atom, $C_F$ - electron concentration in the flux (1/m³), $m_e$ - electron mass (kg), $S$ - atom scattering area (m²), $v$ - conduction electron flux velocity (m/c).

The speed of conduction electrons is determined by the Fermi energy (for Fe $E_T = 11$ eV [12]) and the electron mass:

$$v_F = \sqrt{\frac{2E_T}{m_e}} \ [m/c].$$

When a charged electron particle with a charge $e$ moves in an electromagnetic field, both an electric and a magnetic field will act on it, and the total force is the sum of the forces [13]:

$$\sum F = F_e + F_m = eEZ + Bev_F \ [N],$$

where $F_m$ is the force acting from the constant magnetic field, $F_e$ - force acting from the electric field, $B$ - magnetic induction of the permanent magnet, $v_F$ - the initial velocity of the electron, $Z$ - the number of electric field pulses acting on the electron during its movement in the skin layer [14; 15].

The value $\sum F$ is determined by the electric field strength and the magnitude of the magnetic induction. Using a halogen lamp to generate a given electric field is the most rational choice. Preliminary calculations and experiments showed that 3 halogen lamps with a total power of 6kW create an electric field with a strength of $E = 5000$ V/m and are able to heat a pressed metal powder to 1043 K. A neodymium magnet (magnetic induction $B = 0.5$ T) was used to create a constant magnetic field.

On the other hand, according to Newton’s second law, the force on the electron is proportional to the acceleration of the electron - $a$:

$$F = m_e \cdot a.$$ 

Accordingly, the magnitude of the electron flow acceleration will be equal to:

$$a = \frac{\sum F}{m_e} \ [m/c^2].$$

The final velocity of the electron leaving the skin layer of the metal,

$$v = v_F + at_\delta \ [m/c],$$

in which $t_\delta$ is the residence time of the conduction electron in the skin layer.

It is important to note that the effect of the appearance of an additional driving force is limited by the Curie point (for Fe - 1043 K) [16]. This is due to the fact that overcoming this mark will lead to the fact that the ferromagnet will lose its properties and turn into a paramagnet. In the process of absorption of high-frequency energy, processes of abnormal penetration of free electrons into the metal...
are occurring. The fluxes of electrons transfer their kinetic energy to the atoms of the crystal lattice, pushing them to move into free vacancies, the bulk of which are located in the pores between the powders.

Let us prove the advantage of using this technology in comparison with sintering in a muffle furnace using the example of calculating sintering time at a temperature of 1043 K and a pore radius of 7.217 μm, corresponding to an dispersion of iron powder of 50 μm.

4. Results

After determining the strength of the atomic-electron interaction - $F_a$ by the equation, we can determine the flux of diffusing atoms:

$$J_{AE} = \frac{D \cdot n \cdot F_a}{kT} = \frac{0.51 \cdot 10^{-16} \cdot 6.686 \cdot 10^{28} \cdot 0.062 \cdot 10^{-12}}{1.38 \cdot 10^{-23} \cdot 1043} = 14.7 \cdot 10^{18} \frac{1}{c \cdot m^2}.$$  \hspace{1cm} (10)

In comparison with the fluxes of diffusing atoms due to thermal diffusion and the concentration gradient of vacancies ($J_T = 1.1 \cdot 10^{14}$ 1/m²c and $J_e = 1.21 \cdot 10^{14}$ 1/m²c), the flux due to atomic-electron interaction is decisive for calculating the time of pore overgrowing ($r_p = 7.217$ μm):

$$t_p = \frac{N_p}{\sum J \cdot S} = \frac{23.84 \cdot 10^{12}}{14.7 \cdot 10^{18} \cdot 6.54 \cdot 10^{-10}} = 2480c \approx 0.7hr$$ \hspace{1cm} (11)

Comparison of the obtained value with the duration of pore overgrowth during sintering in a muffle furnace (3.5 hours at a temperature of 1573K) proves the undoubted advantage of using this method.

5. Conclusion

The use of chambers with sources of emitters with a frequency of $\nu = 10^{14} - 10^{15}$ Hz with the simultaneous presence of a constant magnetic field is a promising method for sintering iron-based metallic ferromagnetic powders. During sintering, the effects of abnormal penetration of the electromagnetic field into the metal are manifested, the time of initial heating and further isothermal sintering is reduced. This leads to a uniform temperature distribution, thereby contributing to the achievement of the required quality characteristics of the sintered products.

References

[1] Mironov D.V. et al., Diffusion in under the simultaneous action of a constant magnetic field, the quasi - static and pulsed ultrasonic strain and at room and eleva-


