Application of PTV method for investigation of polydisperse wet steam flow

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Abstract. The paper presents the results of using the PTV method to study the motion of the liquid phase in the interblade channel of the turbine blade cascade in a wet steam flow. A method for processing vector fields of a polydisperse droplet flow is developed on the basis of machine learning algorithms (namely, the Bayesian Gaussian Mixture Data Modeling and the Kernel Density Algorithm). Using the PTV method together with these algorithms makes it possible to study complex polydisperse wet steam flows in more detail. On the basis of this, characteristic droplet streams and their trajectories are determined in the interblade channel of the turbine blade cascade.

1. Introduction
Nowadays laser diagnostic methods are widely used to investigate the aerodynamic characteristics of different objects. The use of particle image velocimetry (PIV) and particle tracking velocimetry (PTV) algorithms requires presence of tracers in the stream. These tracers are usually having an artificial origin.

Low-pressure cylinders of steam turbines operate under conditions of polydisperse wet-steam flow. It leads to a decrease of the efficiency and reliability of the unit. To improve these indicators information about formation and motion of liquid phase are necessary. Complex computational and experimental studies will provide these data.

The application of laser diagnostic methods makes it possible to study the kinematic characteristics of a polydisperse wet-steam flow. These data allows clarifying computational models of wet-steam and estimating efficiency of the active methods of erosion wear reduction. As a result efficiency and reliability of low-pressure flow paths will be improved.

Presence of liquid phase in two-phase condensable medium leads to a number of difficulties in the use of laser diagnostics methods. In the laboratory of Steam and gas turbine department of Moscow Power Engineering Institute (MPEI) laser diagnostic system “POLIS” was adapted to work in a wet-steam flow [1]. The PIV method is widely used to study averaged characteristics of droplet flows [1-4].

The PIV method allows obtaining only the average velocity vector field. This is quite sufficient to qualitatively estimate the efficiency of active erosion reduction methods and determine the average kinematic characteristics of the liquid phase [1-4]. But it becomes a disadvantage in case of complex flows investigation.
To study the structure of liquid phase movement in the interblade channel of the turbine blade cascade, just the PIV method is insufficient. In this case it is necessary to distinguish separate droplet streams, which have a different origin (for example, primary droplets and droplets reflected from the surface of the blade) but move in the same area. Besides, all of these droplet streams are polydisperse. So the droplets with the same origin will have different kinematic characteristics. To solve this problem, the PTV method is well suited. This algorithm finds a pair of particle image on two pictures and determines its velocity vector. As a result, PTV works with individual particles, while PIV defines only the average velocity vector in a unit cell.

The application of the PTV method imposes a number of additional difficulties. The amount of noise encountered in the images introduces an additional error in the calculation of the vector field. Completely remove noise from photos is impossible. One of the reasons is the presence of finely dispersed liquid in the wet-steam flow. These droplets are created naturally due to steam condensation and look like a fog on the photos [4]. Absence of clear images of these droplets leads to incorrectly identified vectors.

This paper is devoted to the creation of the PTV vector fields processing method based on machine learning algorithms.

2. Object of study
In order to obtain the behavior of droplets motion in the nozzle blade cascade, the experimental studies were performed. The investigations were carried out in the experimental facility Wet Steam Circuit (WSC) in the turbine laboratory of the MPEI. This experimental bench is used to study the flow of superheated, saturated and wet steam in stationary channels. Steam for experimental investigations is extracted from the operating steam turbine. It was designed in order to study the polydisperse coarse droplets movement in wet steam flow.

The object of study is the flat stator blade cascade. The geometry of this flat cascade, which consists of 5 blades, is shown in figure 1a.

In order to obtain the characteristics of liquid phase in the blade passage, laser diagnostic system “POLIS” was used. It implements the PTV method that allows obtaining instantaneous velocity vectors for each droplet detected by the method in studied flow domain. The optical scheme of laser diagnostic system is shown in figure 1b. The wet steam flow in the blade passage is illuminated by a plane laser knife formed by a dual impulse laser. It is directed through the endoscope into working part and illuminates droplets moving in the inter-blade channel. Droplets were recorded by the high-speed camera. The obtained droplet flow images are used as initial data for the PTV method. This technique obtains irregular vector field for each pair of photos. In order to increase statistical significance of the results, 1000 photos were made for each studied conditions.

Operation conditions were controlled by measurement of total pressure \(p_0\), total temperature \(T_0\) and initial steam wetness \(y_0\) upstream the experimental cascade and average static pressure \(p_1\) downstream the blade cascade. In this paper operating condition with total pressure \(p_0 = 60000 \text{ Pa}\), initial steam wetness \(y_0 = 3\%\) and theoretical Mach number downstream the nozzle blade cascade \(M_{lt} = 0.8\) has been considered.
3. Methodology of the PTV vector fields processing

Figure 2a presents a photo of liquid particles motion in the interblade channel of the stator blades cascade. Three characteristic regions of droplets movement can be distinguished, two or more droplet stream paths in each of the region. The origin of these streams is different.

All regions contain primary droplets. In regions 1 and 2 there are streams of secondary droplets formed by interaction of primary liquid with the inlet edge of the blade. A lot of droplets interact with the concave surface of the blade. The liquid particles formed as a result of this process move into region 3.

The instantaneous velocity field obtained as a result of PTV processing is shown in Figure 3b. The method of screening by the local average has already been applied twice to these velocity fields. But we still see vectors that are clearly erroneous.

Three areas of 1x1 mm in size are marked in Figure 2b. The dependences of the projection of the velocity vector on the x axis \( c_x \), and on the y axis \( c_y \) are obtained in these areas for 1000 instantaneous vector fields (Figure 3a). The speed changes within the range from -200 to 200 m/s both for \( c_x \) and \( c_y \). It will introduce a significant error in the averaged results. Invalid vectors can be filtered out according to the rule of 3 sigma. It works well with the single-peaked distributions. But in the flow there are droplet streams from different sources. It is clearly seen in histogram shown in Figure 3b. This
histogram displays the number of droplets \( n \), depending on their velocities \( c_x \) and \( c_y \). Thus, it is necessary to separate the error from these results and indicate the sources of droplet streams.

![Figure 3](image)

**Figure 3.** Distribution of droplets velocities along the \( x \) and \( y \) axes (a) and histogram of droplets velocities of \( c_x \) and \( c_y \) (b).

This problem can be solved by applying machine learning algorithms (clustering of the received events in a unit cell). It can distinguish various sources of droplets and separate the error. The algorithms of clustering are divided into two types: with a known number of clusters and with unknown [5]. In this task, the number of clusters is not known. So it is necessary to determine the possible number of clusters, as well as to cluster data.

In the Scikit-learn machine learning library for the Python there are several clustering algorithms. In this work the Bayesian Gaussian Mixture model clustering data was used [5]. This algorithm is the most suitable for solving this problem.

Bayesian Gaussian Mixture is a probabilistic model. It is assuming that all data points are generated from a mixture of a finite number of Gaussian. The Gaussian mixture object implements the expectation-maximization (EM) algorithm for fitting Gaussian models.

The results of applying this algorithm to the mentioned above areas are shown in Figure 4a. The source clusters of the droplets can be determined by combining these results with a histogram. Ovals mark out zones corresponding to clusters of different origin. After this, a nuclear estimate is made of the probability density distribution of the selected clusters. This is done using the kernel density estimation (KDE) algorithm also included in the skikit-learn library [5]. Figure 4b shows the probability distribution densities obtained by this algorithm for these clusters. Local extremums are determined based on these data. These extremums are the starting points for constructing trajectories of droplets of various origin.
Two approaches can be used to build the trajectory: automatic mode and manual mode. The operation principle of the method is shown in figure 5. The results obtained in the first cell are used to initialize the clustering algorithm in the first case. Then the clusters with probability density greater than 0.1-0.2 are determined. These clusters are used to build a probability density function. Extrema of this function are comparable with values in previous cell. The closest one is chosen as the travel direction vector to the next cell. And so it reaches the end of the calculation area until the trajectory. In the second approach, parameters for clustering each subsequent cell and the appropriate extremum are selected manually.

**Figure 4.** Clustering the droplet velocity distributions (a) and selected clusters probability distribution (b).

**Figure 5.** Method to calculate trajectories of droplets.
The result of automatic mode application to estimate droplets trajectories is shown in Figure 6. This data allows determining regions of secondary liquid particles movement. Painted areas correspond to regions of secondary droplets motion. The droplets formed as a result of liquid interaction with the leading edge of the blade move in the blue region. The droplets forming the vapor-drop boundary layer move in the red region. Knowledge about these regions of droplet motion is necessary for the design of new profiles with increased separation ability. It is also important for the design of erosion reduction active methods.

![Figure 6. Trajectories of droplets with different origin.](image)

4. Conclusions
The following conclusions can be made:
1. Combining the PTV and machine learning methods allows studying the structure of droplet streams in interblade channels of steam turbine.
2. The application of this methodology made it possible to identify separate streams of primary and secondary droplets and compute their trajectories.
3. The use of the proposed approach in the long term will allow us to consider in detail the erosion wear of the turbine blades operating in a wet steam flow. And also to optimize the methods of erosion minimization in turbine flow paths.

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