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Exploratory Analysis of Optimisation Results for the Multi-Pump System Using Data-Driven Methods

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Abstract.

Reduced climate impact is a major topic in the mobile machinery industry, and electrification is one of the ways to achieve that. Electrified vehicles provide new opportunities to improve the hydraulic system design to achieve higher efficiency. A Multi-Pump System (MPS) approach has been proposed, that provides connection paths between any hydraulic machine port to any actuator chamber through a manifold of on/off valves. This flexibility provides multiple alternative ways to control the system that are challenging to describe intuitively, specially when multiple actuators are considered. This paper presents an exploration of different machine learning algorithms for data analyses applied to the output of control optimisation of the MPS. The results show that dimensionality reduction might not be enough to provide a visualisation approach with clear borders between operating modes for the design of control rules. A supervised classification approach called *k*-nearest neighbours (kNN) is then trained on the optimisation results to predict the hydraulic machines operating modes based on the actuators' states. Using part of the data for training and testing allows a measurement of the accuracy of this approach. The accuracy of the algorithm varies between 53 % and 96 %, depending on the parameters set for the kNN, greatly reducing the number of options to consider for the design of a control system.

Keywords. Multi-pump system, data-driven analysis, machine learning, dimensionality reduction, classification.

1. Introduction

The global trend of electrification and digitalisation of hydraulic systems brings opportunities for novel subsystems architectures. Electric vehicles provide new degrees of freedom for the design and control of these systems and also require more efficient solutions to minimise the effects of the overall lower energy density compared to fossil fuel alternatives.

Mobile machinery hydraulic systems have traditionally relied on centralised pump architectures, where multiple actuators share flow through proportional valves. When several actuators operate simultaneously, significant energy losses occur due to throttling and flow sharing [1]. Consequently, conventional valve-controlled systems exhibit low overall efficiency. In contrast, a comparative study between a conventional system and a self-contained electro-hydraulic cylinder demonstrated an improvement in efficiency from 22 % to 57 % [2].

An electrified vehicle can adopt similar solutions to those applied to combustion engines, such as displacement control [3, 4]. The disadvantage is that the hydraulic machines share a single shaft, limiting their operation to the same angular speed, thus variable displacement is needed. Electro-hydraulic actuators (EHAs) aim to decentralise the hydraulic system and eliminating flow sharing between actuators can improve efficiency [2, 5, 6]. The downside is the increase in total installed power, as each EHA must be sized to provide the maximum corresponding actuator power.

Common- or multi-pressure rail solutions can also be employed [7–9], but they typically still required some level of throttling for finer control, although a more recent proposal aims to achieve varying pressure levels [10]. Finally, a novel solution proposes a network of variable-speed drives to control the hydraulic machines for multi-actuator operation and to remove the directional valves [11–13], although sizing components and defining the ideal short-circuits between actuators' chambers is non-trivial.

This paper focuses on another proposal called the Multi-Pump System (MPS) [14]. The system aims to minimise throttling losses by using only on/off valves and focuses the control system on the variable-speed, fixed-displacement, 4-quadrant operation pump/motors. Since the hydraulic machines can be shared between actuators and recuperation and regeneration are available, the total installed power can be reduced.

Controlling such a system is challenging, as there are many options to achieve the same behaviour. An optimisation strategy available in [14, 15] determined the operating conditions that minimise power consumption for a system with a single actuator. The results can be used to define the optimal operating conditions for the hydraulic machines based on the actuator's speed and force. Visualising the data and extracting control rules for this system is intuitive [16], but each additional actuator doubles the number of dimensions to consider.

1.1. *High-Dimensional Control Challenges in the Multi-Pump System*

Figure 1.1 shows an example of the MPS, referred to as 3P2A, with three pump/motors (3P), two actuators (2A), and a constant pressure source for the low-pressure line. The valve manifold allows any pump/motor port to connect to any actuator chamber. By sharing the hydraulic machines between the functions, the overall installed power can be reduced compared to alternatives such as individual electro-hydraulic actuators. The system design facilitates expansion, meaning that more actuators or hydraulic machines can be considered, which only requires adding a row or column of valves, respectively, for each new component [14].

One drawback of this solution is that the control strategy is tightly coupled to the operating state of each system component. The number of active hydraulic machines and their operating modes (pump or motor) depend on the combined operating quadrants of the actuators throughout the drive cycle. In theory, flow distribution among the hydraulic machines can be achieved in infinitely many ways, and should account for energy recuperation and regeneration, leading to a large number of possible configurations.

Previous research discussed how an optimisation approach can be used to explore the control variables design space [14, 15]. Based on the actuator(s) operating points, the algorithm can identify what are the optimal ways to distribute the flow throughout the system during steady-state operation to minimise power consumption. The goal is to identify unusual valve connections and define transition boundaries that determine when to activate the hydraulic machines and how to distribute the flow between them.

The design space is reduced, but remains high-dimensional and difficult to interpret. As a result, direct visualisation of the results might not be possible, and more structured analyses are required. This paper presents an exploratory application of established machine learning techniques for high-dimensional data analysis to use the optimisation results.

The characteristics and algorithms of the applied methods are not discussed in detail, as they are will established in the literature. Mathematical descriptions and examples are provided in [17, 18], while practical implementations in *Python* are presented in [19]. The methods used

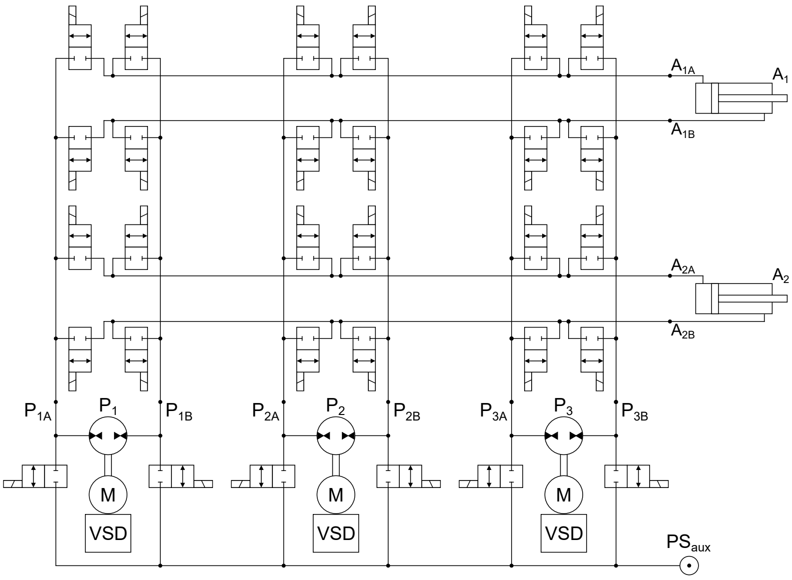


Figure 1.1: A 3P2A Multi-Pump System with three pump/motors, two actuators and a constant auxiliary pressure line.

in this work are available in the *Scikit-learn* library [20], and the following descriptions are based on these references unless stated otherwise.

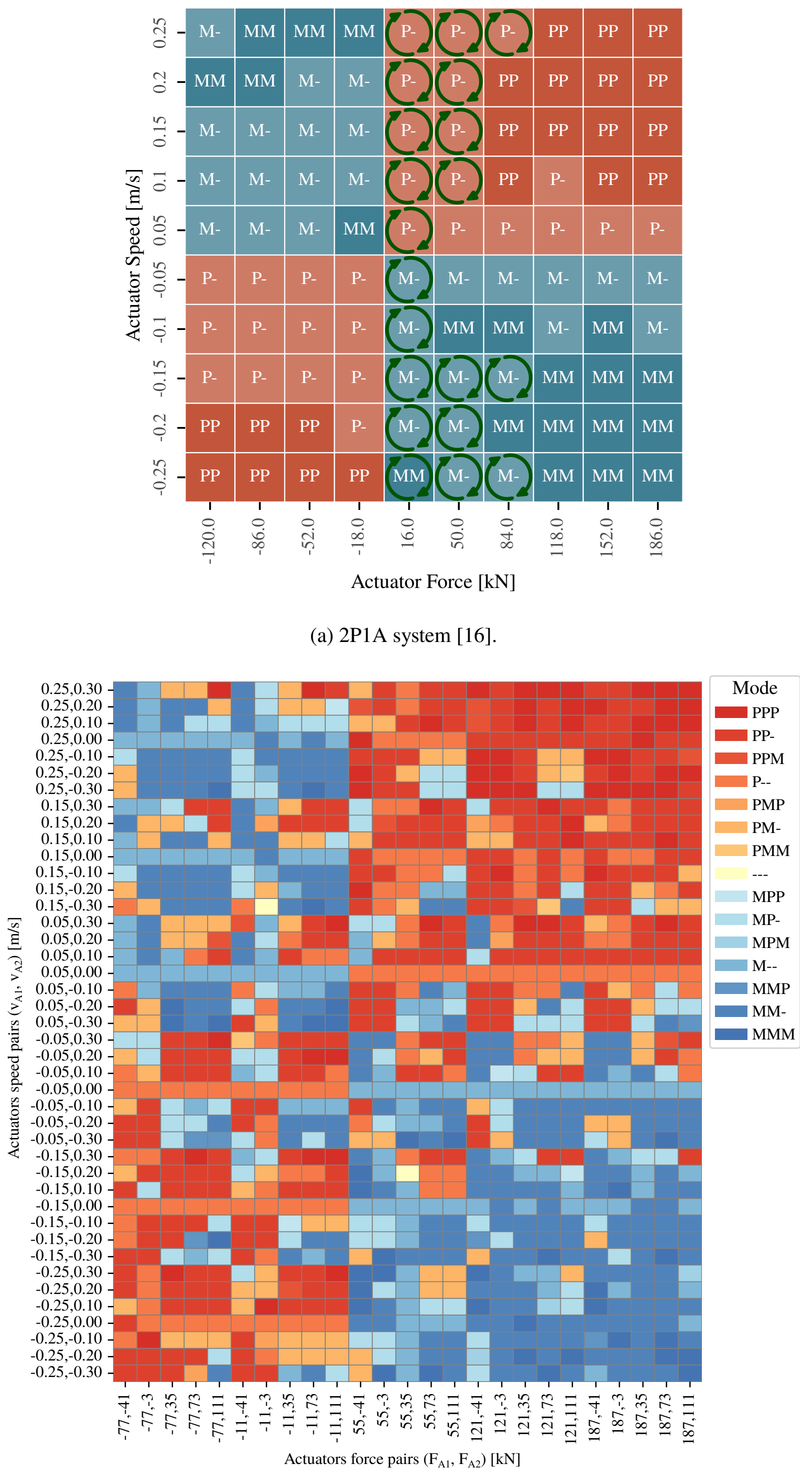
2. Problem Statement and Motivation for A Machine Learning Approach

For a system with a single actuator, the transition boundaries between operating modes are straightforward to define due to the low-dimensional operating space, as illustrated in fig. 2.1a for a 2P1A system. The axes represent the desired actuator speed and force–which can be determined from the chamber pressures and the corresponding actuator areas (piston- and rod-side).

Each speed-force combination corresponds to an optimal operating mode for the two hydraulic machines, found by the optimisation algorithm. The two letters shown in each cell refer to pump/motors P_1 and P_2, respectively: "P" indicates pump mode, "M" is motor mode, and "-" an inactive machine. The green arrows indicate regenerative mode, when the actuator chambers are short-circuited to reduce the required pump/motor flow. The resulting division enables the design of a mode-based control strategy, where control decisions depend on the region in which the operating point lies.

Figure 1.1 illustrates a system with an additional actuator and one more pump/motor, a 3P2A configuration. To maintain a high degree of freedom for control, the pump/motors are sized so that two can provide the maximum combined actuators' flow. The third machine, of identical size, provides redundancy and allows the system to achieve high actuator velocities without requiring all three machines to operate at high angular speeds.

The additional actuator introduces two extra dimensions to the input space. To reduce the visualisation to two dimensions, a representation similar to Fig. 2.1b can be used. In this graph, the x-axis represents pairs of actuator speed values: the first actuator's speed is held constant while the second actuator's speed is varied across its discrete values. Once all values for the second actuator have been covered, the first actuator's speed is incremented to the next grid level, and the process repeats. The same approach is applied to the force values.



(a) 2P1A system [16].

(b) 3P2A system [14].

Figure 2.1: Optimal operating modes for two MPSs architectures: (a) 2P1A and (b) 3P2A systems.

The optimisation can assign any of the pump/motors to operate at each evaluated point, which may result in functionally redundant solutions—for example, the operating modes `P--`, `-P-`, and `--P` all represent the same system behaviour. To address this, the solutions are reorganised such that the first character always corresponds to the pump/motor with the highest absolute angular speed, which can be assumed to be P_1 in Fig. 1.1. For instance, a mode like "-PM" would be reordered as "MP-", indicating that the machine with the highest angular speed operates as a motor, the second as a pump, and the third is inactive.

The previous step reduces the number of combined operating modes to consider, but defining transition criteria from the resulting graph remains challenging. While the corner regions are relatively easy to interpret, the intermediate areas exhibit more complex and irregular boundaries. This lack of clear separation makes it difficult to extract consistent rules solely from the graph. Alternative arrangements of the axes values were tested, but they did not lead to significant improvements in interpretability.

Hydraulic systems for mobile machinery often have three or more actuators, increasing the challenge of defining the transition criteria. It is thus interesting to apply methods that can adapt to a varying number of input variables, or for the purposes of using machine learning terminology, the features or dimensions of the problem.

2.1. *Selected Machine Learning Methods*

Different machine learning algorithms could be employed to undertake this problem, which depends on what the aim is and what information one wants to employ for the analysis. The proposal for this paper can be summarised in the following questions:

- Which machine learning methods should be employed for the MPS problem based on the optimisation results?
- Assuming a system plant with limited sensors and a direct application to a control system using only the measurable variables such as actuator speed and pressure levels:
  - Is it possible to summarise the available information into a bi-dimensional representation that can be used as a guideline for the definition of rules and transition regions for a control system?
  - Can any method produce a model from the optimisation data available that can take the necessary control decisions with satisfactory precision?

The results presented in this paper therefore focus on two complementary approaches. The first considers dimensionality reduction approaches, which can be used for visualisation of patterns in the data in lower dimension or to produce a simplified model of the system. The second approach relies on supervised classification algorithms. As the operating modes are already defined by the optimisation procedure, they can be treated as class labels, enabling the algorithms to categorise the data based on the available input variables.

The following sections present results for the two approaches. The algorithms applied here were selected for their illustrative value and are not necessarily optimal, as the best choice depends on the specific problem context. This paper focuses on the dimensionality reduction techniques Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), as well as the supervised classification algorithm *k*-nearest neighbours (kNN).

2.2. *The Optimisation Results*

The Genetic Algorithm (GA) employed to produce the data used in this analysis is described in [15]. A similar process is done for the 3P2A system with varying actuator speeds and force levels. The goal of the optimisation is to minimise power consumption at steady-state, thus transitions between operating modes and valve switching are not accounted for.

The optimisation is performed six times for each combined operating point of the actuators in order to limit the computational cost. The reason is that the GA is used as a stochastic, explorative method and does not guarantee global optimality. Instead, this optimisation problem can exhibit multiple local minima with similar performance. From a control perspective, having multiple feasible solutions is advantageous, as it provides flexibility when selecting operating modes and transitioning between configurations. The operating modes presented in fig. 2.1b refer to the best solution of the six runs.

The combined actuators' operating points, as shown in fig. 2.1b produced a total of 1 050 points, thus totalling 6 300 optimisation runs. The values of all system variables are available for analysis. Around 2,6 % of these points are discarded as they converged to undesired operation conditions, e.g. with too large error in the actuators' speeds. Thus, the following methods are applied to a data set with a total of 6 134 points.

The 3P2A has at least four features, corresponding to the force and speed of each actuator, but more could be employed. Assuming that in a real system only pressure levels can be measured, the following results use the actuators' reference speed values and pressures on each chamber as the features for analysis. The aim is to evaluate whether this feature set is sufficient to support control decisions at pump/motors level.

3. Dimensionality Reduction for Visualisation

The main idea with dimensionality reduction is to represent a high-dimensional data set into fewer dimensions. Some methods focus on identifying redundant aspects of the data set that have minimal effect on the distribution and thus could be ignored without high loss of information. Figure 3.1 summarises the process employed in this work.

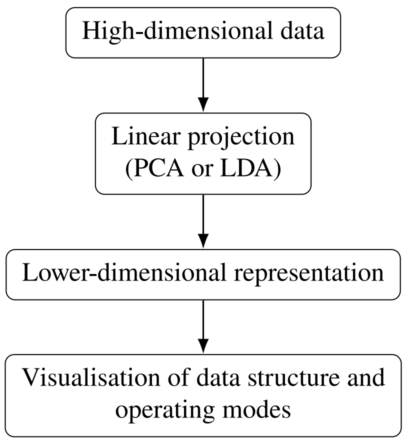
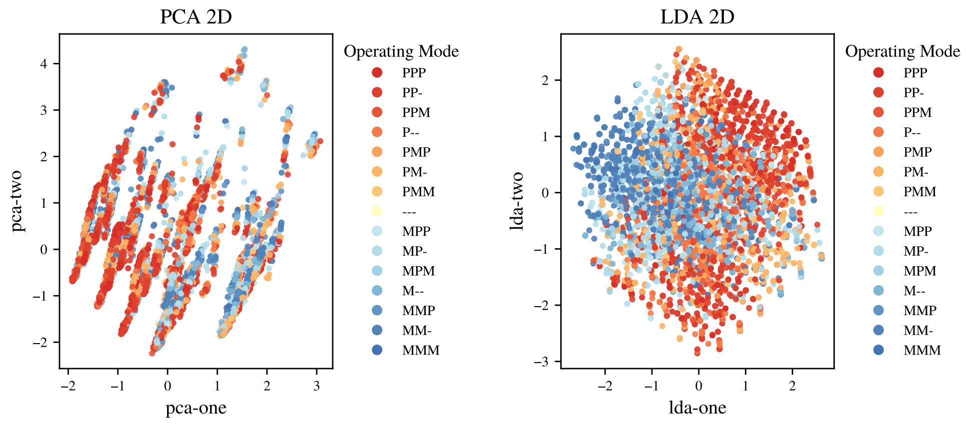


Figure 3.1: Overview of the dimensionality reduction workflow using PCA and LDA.

PCA and LDA are both dimensionality reduction techniques. They create new variables—linear combinations of the original features—that aim to represent the data in fewer dimensions. PCA is an unsupervised method that identifies directions of maximum variance in the data, thereby spreading the data points as widely as possible. LDA, on the other hand, is a supervised technique that uses known class labels to find directions that maximise the separation between classes. Although LDA can also be used for classification, it is often use for dimensionality reduction in a way that preserves the separation.

As these are linear methods, it is also possible to determine the features values from a data point in the lower dimension space. This could be used to determine the operating modes for a point that was not evaluated during the optimisation. Their downside is that the linear approach may not capture the non-linear characteristics of the system, thus underperforming regarding the data separation. Nevertheless, they can provide simple models from a data set with a large number of inputs.

Figure 3.2 shows the two-dimensional projections obtained by using the first two components as the x- and y-axes for both PCA and LDA. In both cases, the first components describe the dominant structure of the data, which results in the most distinct separation. Figures 3.2a and 3.2b show the resulting data clustering for PCA and LDA, respectively.



(a) Principal Component Analysis (PCA).

(b) Linear Discriminant Analysis (LDA).

Figure 3.2: Visualisation of the first two components for the dimensionality reduction algorithms.

From these results, limited information can be extracted from visualisation alone, although some initial clustering can be seen. Table 3.1 shows the explained variance (*PCA Var. Ratio*) and cumulative explained variance (*PCA Cum. Var.*) for each PCA component, as well as the equivalent discriminant ratios (*LDA Discr. Ratio*) and cumulative discriminant ratio (*LDA Cum. Discr.*) for LDA. There are a total of six features, the actuators' speeds and the pressure levels in each chamber. Accordingly, PCA can yield up to six components, while LDA produces at most one fewer discriminant component than the number of classes.

Table 3.1: Explained variance ratios for PCA and discriminant ratios for LDA, including cumulative values.

Component	*PCA Var. Ratio*	*PCA Cum. Var.*	*LDA Discr. Ratio*	*LDA Cum. Discr.*
1	0,22	0,22	0,77	0,77
2	0,19	0,42	0,13	0,90
3	0,19	0,60	0,06	0,96
4	0,17	0,77	0,02	0,98
5	0,17	0,93	0,02	1,00
6	0,07	1,00	-	-

The first two PCA components explain just 42 % of the total variance in the data, indicating that a two-dimensional projection provides a limited representation of the data, as in fig. 3.2a. LDA, on the other hand, captures 90 % of the cumulative discriminant ratio with the first two components; however, this does not translate into clear visual separation due to the large number of operating-mode classes and their possible overlap.

Overall, neither method yields a two-dimensional representation with clear separation between operating modes. This might be expected, as the analysis attempts to determine the pump/motor operating modes based only on actuators information, thus neglecting non-linear behaviour and discontinuous characteristics of the system.

4. SUPERVISED CLASSIFICATION WITH K-NEAREST NEIGHBOURS

An alternative approach is to use the operating modes obtained from the optimisation to train supervised classification methods. Once trained, these models can predict the pump/motor operating modes (classes) based only on the input variables provided during training.

The k-nearest neighbours (kNN) algorithm is selected due to its simplicity and intuitive interpretation. For a given input point, the algorithm identifies the k closest points in the training data and assigns a class based on a majority vote. Two weighting strategies are considered: uniform weighting, where all neighbours contribute equally, and distance-based weighting, where closer neighbours have a stronger influence. Distances are computed in the multi-dimensional feature space, allowing the method to incorporate multiple input features simultaneously. Figure 4.1 presents the steps employed in this paper, and section 4.1 expands on these steps.

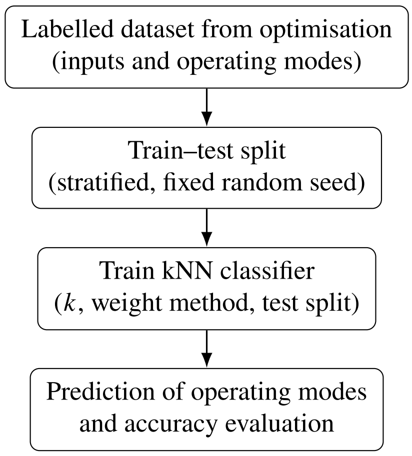


Figure 4.1: Overview of the supervised classification workflow using kNN.

4.1. *Accuracy Evaluation and Hyperparameters*

The classification accuracy is evaluated by dividing the dataset into separate training and test sets. The trained model is applied to the inputs of the test set, and the predicted operating modes are compared with those obtained originally from the optimisation.

To ensure that that all operating modes are accounted for during training, a stratification approach is used to ensure that both training and test sets contain examples of each class. Therefore, the data split is generated through a randomised procedure with stratification, and a fixed random seed is used to provide the same train-test separation when comparing results with different hyperparameters.

The parameters used and varied for the kNN classifier are:

- **Number of neighbours:** $k = 5$.
- **Weighting method:** uniform or distance.
- **Test set fraction:** 10 %, 20 %, 30 %.

The small number of neighbours was chosen to prioritise local information. Since several operating modes occur infrequently in the dataset, using a small k reduces the influence of frequent classes and distant samples, thus mitigating misclassification of rare operating modes.

4.2. *Classification Results*

Table 4.1 shows the accuracy for different evaluations with kNN using the unmodified optimisation data. One characteristic of the MPS is that it might have multiple viable solutions for each combined operating point of the actuators. In the table, the *Exact* column refers to the kNN accuracy in finding the exact operating mode determined by the optimisation runs in the test set.

The results are also presented for the training and test sets. Using the same training set to evaluate the kNN serves as a sanity check on the model memorisation. Generalisation is assessed from the test set.

Table 4.1: Comparison of kNN classification accuracies (%) for different test set sizes and weighting methods. Exact = strict accuracy, Accept. = acceptable accuracy (any valid mode for same operating point), Top-3 = accuracy within three most probable modes.

Split	**Uniform weights**			**Distance weights**		
	Exact	*Accept.*	*Top-3*	*Exact*	*Accept.*	*Top-3*
Training set						
10 %	68,3	95,2	99,8	100,0	100,0	100,0
20 %	67,6	94,3	99,8	100,0	100,0	100,0
30 %	67,5	93,2	99,7	100,0	100,0	100,0
Test set						
10 %	54,2	90,2	98,5	58,3	94,6	98,5
20 %	54,0	89,2	98,7	58,2	95,3	99,0
30 %	53,2	86,6	98,9	57,9	94,9	99,2

In this context, the distance-weighted approach may not be ideal. If two optimisation runs converge to the same mode for a given operating point of the actuators, the features used for training may be identical due to model simplifications. Consequently, the test point for the kNN algorithm may exactly match one of the training points, resulting in nearly zero distance, as the points coincide in the feature space. This explains the 100 % accuracy for the training set in tab. 4.1.

For the *Exact* columns, the accuracy varies between 53,2 %-68,3 %, which could be misleadingly low. Since multiple solutions are viable, a more reasonable approach would be to evaluate if the kNN determines any of the operating modes that the optimisation found for the corresponding operating point of the actuators. These are the values in the *Accept.* columns, increasing the accuracy to 86,6 %-95,3 %. This reflects the case where multiple operating modes are interchangeable from a control perspective.

The kNN output is also not a single value, but rather a probability for each of the possible classes. For a given actuator operating point, the highest probability mode from the kNN may not match the one found by the optimisation, but the second or third most likely class might. This is shown in the *Top-3* column, which verifies whether any of the most probable classes selected by the kNN corresponds to the optimisation result, moving the accuracy to 98,5 %-99,8 %.

5. DISCUSSION

The kNN classifier is a viable approach for predicting the operating modes of hydraulic machines. Using only reference speeds and chamber pressure values—which can be available in real applications—the algorithm can estimate the hydraulic machines' operating modes with acceptable accuracy when appropriate considerations are taken into account.

Using the ranked output of the algorithm, based on neighbour votes, can also be helpful for the control design. It greatly reduces the number of options to consider, making it possible to efficiently evaluate which of the options would lead to fewer transition losses.

A current limitation of this approach is that the hydraulic machines operating modes do not cover short circuiting actuator chambers. In a dynamic system, if the external force changes, the pressures will vary according to the current valve combination. The kNN would then provide the operating mode that best fits the current valve setting.

Future work could therefore perform a similar analysis but focused on the valve signals, define operating modes for the actuators, or determine short-circuited chambers from the optimisation results. A separate kNN, or other algorithm, could then be employed to find the viable system connections.

The dimensionality-reduction methods were also evaluated as potential preprocessing steps. While PCA maximises variance and LDA maximises class separability assuming linear projections, neither method improved the separability of operating modes in lower-dimensional spaces for the kNN. This suggests that non-linear relationships in the system play a significant role in determining the operating modes.

The next step is to apply the proposed classification to a dynamic model to evaluate how well the control system will perform. This includes setting criteria to select the operating mode based on neighbour vote confidence of the kNN and evaluating the model's ability to interpolate operating-mode decisions for actuator conditions not covered during training.

5.1. *Other Machine Learning Methods and Possible Applications*

Other machine learning methods exist but were not considered in this work. Unsupervised clustering and classification are not suitable in this case, as the classes-corresponding to operating modes- are already defined based on the torque and angular speed values obtained from the optimisation.

Neural networks and reinforcement learning are also commonly used approaches but were outside the scope of this study. These methods typically require large datasets for training, and parameter tuning is challenging as they are, in a way, complex optimisation problems. One of the objectives of this work was to identify a compromise between model capability and practical application, favouring methods that are easier to implement while still capable of supporting the control decision process.

Regression methods were also considered but not explored in this paper. No satisfactory compromise was found for the development of a simple yet reliable model based on limited inputs. A possible explanation is that information from the actuators is transmitted to the pump/motors through the valve manifold, and relevant details are lost when valve states are not included. This does not mean that the approaches are not viable, but rather that a more detailed analysis is required.

6. CONCLUSION

A Multi-Pump System poses a combinatorial control problem due to the large number of possible connections between hydraulic machines and actuators. While optimisation can identify power-efficient operating modes, the direct use of optimisation results in a control strategy is impractical.

This work showed that linear dimensionality-reduction techniques such as PCA and LDA are insufficient to achieve a clear separation of operating modes for a 3P2A MPS, due to the non-linear characteristics of the system. This motivated the use of a supervised classification approach. A kNN classifier was therefore applied to map operating conditions to operating modes. The achieved accuracy ranged from 53.2 % to 99.5 %, depending on whether exact operating mode prediction or the identification of a feasible alternative was required.

The results show that, although low-dimensional projections are insufficient for direct interpretation, supervised classification can be used as a tool to analyse and structure optimisation outcomes. Further work is required to assess the robustness of this approach for operating points outside the training data and to evaluate its relevance when applied in a dynamic or control-oriented context. In addition, the current approach does not address other aspects of the control process, such as valve configurations or the conditions to short-circuit actuator chambers, which might be necessary for a effective design of the control system.

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