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Origin Destination matrix estimation and prediction in vertical transportation

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ABSTRACT

The dispatching algorithm serving in a building with more than one lift can use passenger flow detailed information based on the requests made by the passengers to go up and down in order to improve the performance of the system. The requests can be analysed in order to extract detailed information about passenger arrival and destination floors and that information used to improve lift assignments. The control strategy can be optimised to look for ways to react to changes in traffic flow. In this paper the traffic flow is described as detailed origin-destination matrixes for 5 minute time intervals. The passenger flow analysis process is divided in two steps, first passenger detailed counting and then, a forecasting process applied to the data coming from the first step. For the first step, the passenger counting process, data obtained from a typical multi-storey office building is used and the results compared with actual manual counts from the same building. After this validation process, the next step uses the data as time series where prediction methods can be applied. Prediction methods can forecast the next time interval traffic flow. Neural networks are able to approximate different time series and are used in this paper with two different data resolution entries, 5 minute interval data and 2.5 minute interval data. The results of both forecasts are compared at a resolution of 5 minutes, and the results show that a methodology of working at a higher resolution to later aggregate the result at a lower resolution can be useful in this context.

INTRODUCTION

A LGCS (Lift Group Control System) serving in a building with more than one lift can use passenger flow detailed information in order to improve its performance. This information can be used to improve assignments of passenger requests to the cabs. Using detailed information about passenger arrival and destination, the optimal route selection process will be dynamically improved. With this information, the service that the system is giving to the lift passengers can be improved. It can also be helpful to understand the building needs and to improve the management of the resources it has. As an example, some lifts can be temporarily out of order or travel at different velocities according to the passenger requests and minimum service levels. It is also expected that improving the planning will move more people per time unit. This paper shows some empirical results obtained across the passenger origin destination counting process. Passengers moving through a building are manually counted and the passenger profile of the building created using Elevate^{TM} simulation software. After this, the profile has been used to generate a log data file and this data used as an entry for an algorithm that performs the passenger counting as suggested in [1]. The validation process compares these two different passenger flows, the first coming from manual counting and the next extracted from the log data generated by Elevate^{TM}. These two different counts are used for comparison purposes and as a validation process in order to assess the accuracy of the log based passenger counting algorithm that we have implemented.

The information extracted from this first process is very detailed and can be useful for the next step, the prediction step. Although neural networks have been widely used for predicting incoming passengers and the next stopping floor, in this case, some different neural network topologies are going to be used to predict each origin and each destination of the passenger flow. We will try two different information entries to the neural network, with data at different resolutions. The output from both of the entries will be used later to validate the prediction step using data from the real count.

PASSENGER FLOW AND DETAILED COUNTING

When the passengers travel in multi-storey building using lifts, they use the up and down call buttons of a lift system to register landing calls. These landing calls are assigned to one lift by a control unit called a lift group control system (LCGS). The information about the requests and the number of passengers boarding and alighting for each stop can be recorded and this data used to extract passenger flow patterns specific for the building. The passenger flow can be converted into origin destination matrices. These matrices show the number of passengers moving from one origin of the transportation network to a destination for a period of time.

We will demonstrate an example of the information extracted for one 5 minute time interval, presented in an origin destination (OD) matrix for an 11 floor building. Each row in this matrix shows the number of passengers moving from the origin floor corresponding to the row number, to the destination floor corresponding to the column number. The matrix is first filled with 0s; the diagonal of the matrix, 0-0, 1-1, 2-2, etc. is always 0 because in a journey there is no passenger going to and from the same floor. Consider that there is a passenger on the floor 2nd who wants to travel to the 10th floor, 3 passengers travelling from floor 3rd to 9th, and 2 passengers travelling from floor 5th to 11th. If the building has 11 floors the OD matrix will be as shown in Figure 1.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	**1**	0
3	0	0	0	0	0	0	0	0	**3**	0	0
4	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	**2**
6	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0

Figure 1: An origin destination matrix (OD) of a up journey with 6 stops, people board on 2th, 3th, 5th floors and alight at 9th, 10th and 11th.

In order to fill the OD matrices, the principle of the conservation flow is applied and linear equations are solved for each lift journey. A journey can be understood as a trip of one lift, where people travelling in the same direction use the cab, boarding and alighting but all in the same direction.

A journey finishes when the direction changes or the lift has no requests to attend to for a period of time. The information about how many people are moving from floor to floor in each journey is then aggregated for all the cabs and processed for each time interval, 5 minutes or 2.5 minutes.

A system that wants to perform this counting has to complete the next steps:

1. Divide the log data, for the time period needed, in our case it was 5 minutes (also 2.5 minutes for forecasting purposes).
2. For a given period, separate the lift movements into journeys.
3. From those journeys, the following information is collected every time the lift stops:
    - Number of passengers leaving and entering the lift at each floor. To obtain this number it is necessary to have three weight measures, just before the lift arrives at the floor where it is going to stop, after the passengers leave the lift and after the lift has left the floor. The information about the number of passengers boarding and alighting can be extracted from weight sensor data or maybe the processing of camera information.
    - Time stamp associated with the landing calls coming from this floor.
    - Car calls that have been registered after leaving that floor.
4. The principle of passenger flow conservation equation, says that the number of passengers entering and leaving a lift during a journey is equal. Using that principle, it is possible to estimate the missing information about the real passenger movements in the journey. This calculation has been done using the symbolic calculation module of MATLAB. In some cases, some rules, extra rules, are needed to be applied in order to solve the equations. These calculations are completed for all the journeys across all the lifts.
5. Information about the timestamp corresponding to the first request of the journey has to be collected to later aggregate the passenger movements across all the lifts for the five minutes time intervals. The final value is obtained by aggregating from the same time interval the different journey data in one OD matrix and then, aggregating the OD matrices of the different lifts.

Data collected manually in a London office building with 12 floors and 8 cars has been used to generate an Elevate^{TM} profile. From that profile, a log file has been obtained after processing the passenger requests and this information given as an entry to the passenger counting estimation process. The data processed was from 10:30 to 12:50 in the morning, and the Figure 2 shows the manually counted number of passengers entering the building and the results of the estimation process. The results of the 5 minutes passenger origin destination flow are aggregated to extract the incoming passenger flow for comparison with the manual count.

The X axis runs from 1 to 29, the number of 5 minute intervals between 10:30 and 12:50, have both been included. There were a total of 1015 passengers manually counted as incoming flow and we were able to detect 960, corresponding to an accuracy of 95%. We lost some journey data because the movement complexity of some journeys was impossible to solve. They were so complex that the symbolic equations could not be solved. It is possible that some additional rules could be added to achieve a better fit.

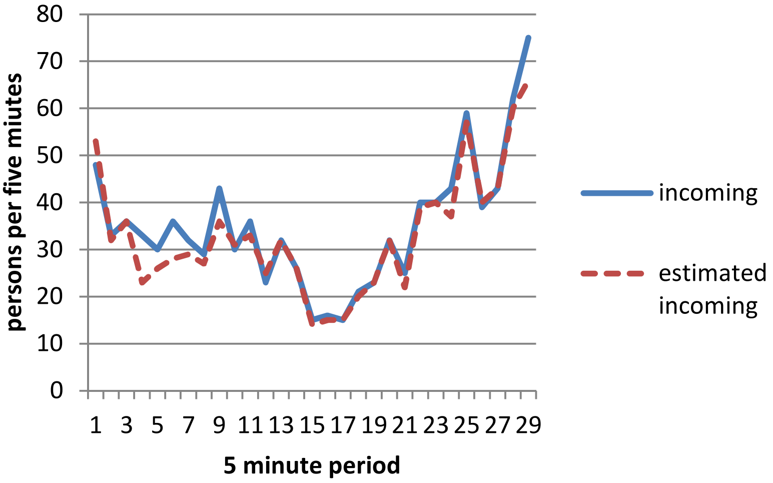


Figure 2: The number of real passengers entering the building and the estimated number of passenger incoming.

Regarding the outgoing traffic, Figure 3 shows the comparison between the real counting of the number of passengers that are leaving the building, and the estimated ones. In this case, the total number of passengers leaving the building was 1152 and we were able to detect 1087 of them, with an accuracy of 94%.

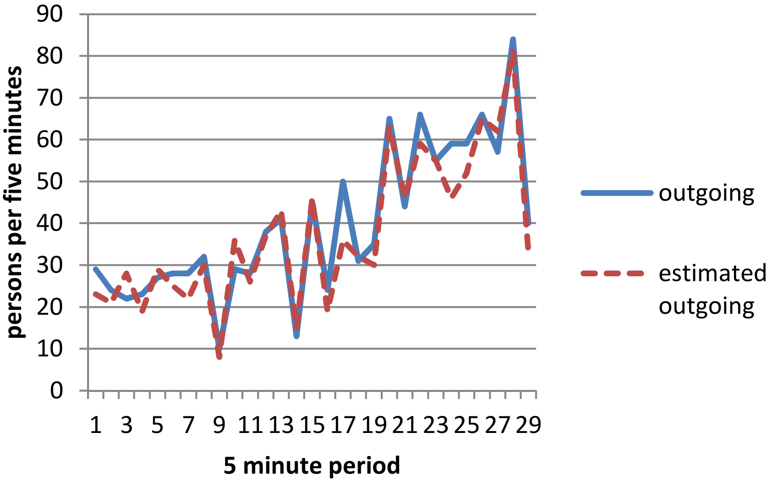


Figure 3: The number of real passenger leaving the building and the estimated number of passenger outgoing.

In order to complete the next step, the forecasting, the data has to be disposed as measures at regular intervals of time. The number of passengers moving from one floor to another (132 combination, excluding the ones that are not possible to and from the same floor), measured along the 29 intervals of 5 minutes and ordered over time are shown in Figure 4.

We have 132 different time series and 29 measures, at consecutive time intervals, for each one. The objective of this step will be to use a number *h* of previous time intervals for each time series to forecast the next value. As an example, one time series that represents the number of passengers moving from floor 2 to floor 6, have the next values: 6, 5, 4, 3, 0, 1. It has to be understood that 6 passengers has gone from 2nd to 6th in the first time interval, t_1, 5 passengers in the next time interval, t_2 and so on. Generalizing we can talk about the X time series as a sequence of values registered at regular time intervals.

$$X = x_1, x_2, x_3, x_4, \ldots\ldots, x_n$$

FORECASTING

Traffic flow forecasting is the core of the transport planning and traffic control. There are a lot of forecasting methods but it is important to know the nature of the data and try to select a method that can be appropriate for the task in hand. Traffic flow data features are nonlinearity and strong interferences.

The forecasting task can be tackled in different ways. Some of the methods [3] only try to train the system to identify a possible congestion with algorithmic methods. Others understand the data as a time series and use some signal processing methods [4] or box-jenkins methods [5] to do the forecasting. Support vector machines has been used also [6] for this task. A brief table, with the advantages and disadvantages of some methods can be seen in the table 1.

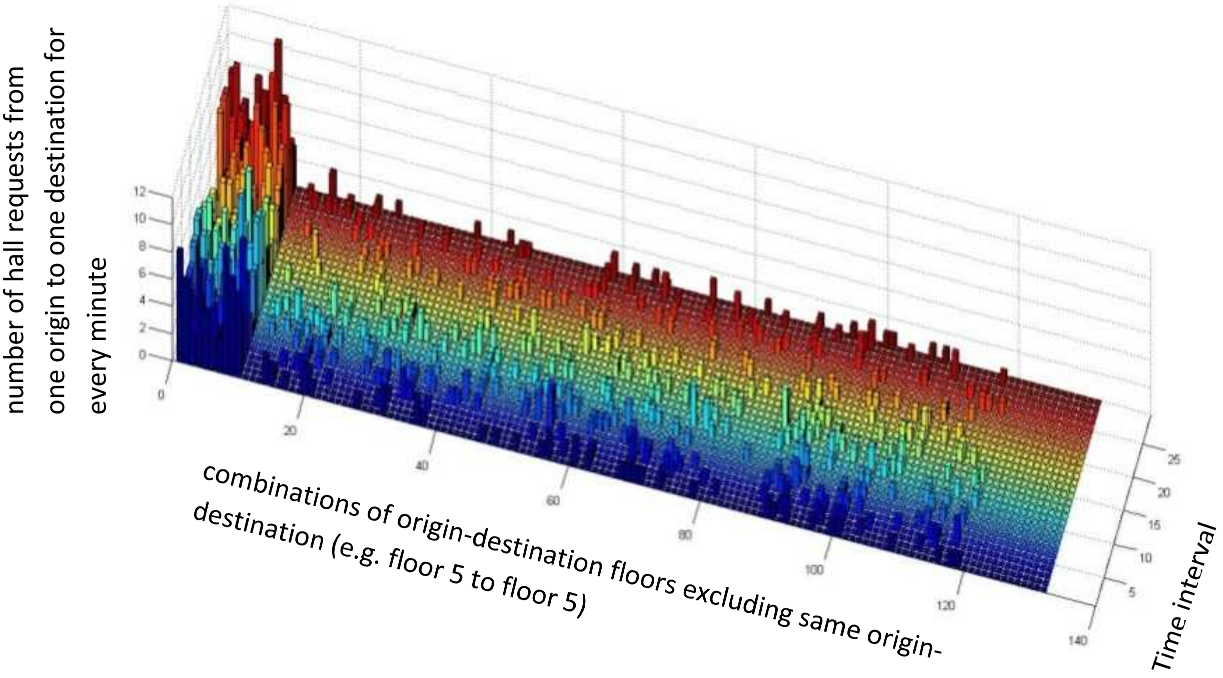


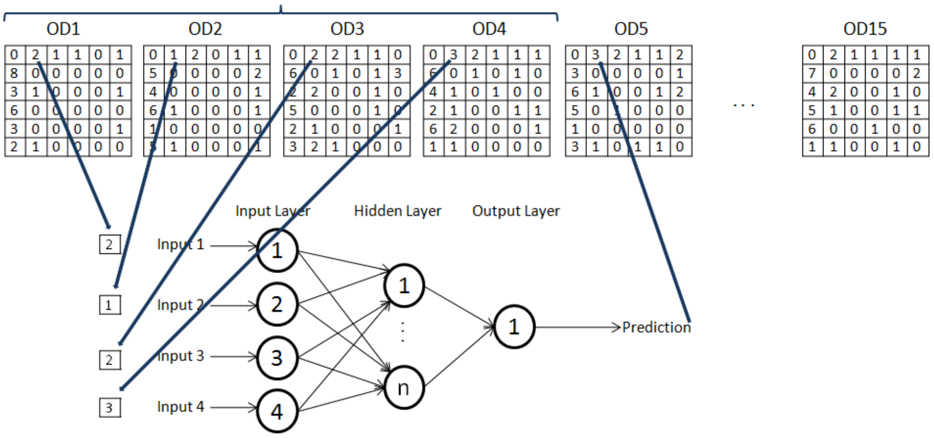
Figure 4: A bar plot of the requests for the 132 combinations (12*12 floors excluding the requests from one floor to the same) across the 29 five minute intervals.

Table 1 : Advantages and disadvantages of some forecasting methods

Methods	Advantages	Disadvantages
Moving Average	Simple	Not Good Fit
Arima	Good Fit	Tedious Programming
Kalman Filters	Good Fit	Tedious Programming
Bayesian Networks	Good Fit	Tedious Programming
Artificial Intelligence & Neural Networks	Well known	Fall In Local Minima
Support Vector Machines	Forecasting Of Small Samples	Sensitive To The Selected Kernel Function
Wavelets & ARIMA	Wavelets Have Good Decomposition Power And ARIMA Good Linear Fitting	Tedious Programming

Using soft computing methods, like Neural Networks, it is possible to train a network with information about how many passengers have requested a lift trip from one floor to another and then expect the network to predict the number of passengers that are going to make the same request for the next time interval.

The topology of the neural network is a question that can be discussed. In this work we are going to use quite a simple topology, where the input layer is going to have *h=4* neurons and the hidden layer is going to have 10 neurons. The output layer will have only 1 neuron. The neural network will be trained with the previous 4 values, x_{t-4} $x_{t-3,}$ $x_{t-2,}x_{t-1}$, , and the result of the neural network will be x_t. Figure 5, shows this structure and the relationship with the OD matrices. 132 different neural networks were created and trained with requests data specific to each origin and destination and the previous 30 intervals time data used for the neural network training. After that, 14 consecutive time intervals data are given to the neural network as an entry and the prediction results used to evaluate the forecasting step.



OD1

0	2	1	1	0	1
8	0	0	0	0	0
3	1	0	0	0	1
6	0	0	0	0	0
3	0	0	0	0	1
2	1	0	0	0	0

OD2

0	1	2	0	1	1
5	0	0	0	0	2
4	0	0	0	0	1
6	1	0	0	0	1
1	0	0	0	0	0
5	1	0	0	0	1

OD3

0	2	2	1	1	0
6	0	1	0	1	3
2	2	0	0	1	0
5	0	0	0	1	0
2	1	0	0	0	1
3	2	1	0	0	0

OD4

0	3	2	1	1	1
6	0	1	0	1	0
4	1	0	1	0	0
2	1	0	0	1	1
6	2	0	0	0	1
1	1	0	0	0	0

OD5

0	3	2	1	1	2
3	0	0	0	0	1
6	1	0	0	1	2
5	0	1	0	0	0
1	0	0	0	0	0
3	1	0	1	1	0

OD15

0	2	1	1	1	1
7	0	0	0	0	2
4	2	0	0	1	0
5	1	0	0	1	1
6	0	0	1	0	0
1	1	0	0	1	0

Figure 5: Structure of the Neural Network

Figure 6 shows an example of real requests coming from one origin and going to one destination, in blue, and the predicted requests for the same origin and the same destination, in red.

The methodology used for the forecasting approach was to work at two different resolution levels and to compare both sets of results. Working with detailed passenger flow data facilitates this approach because detailed data about each journey is available. Five minute interval forecasting is understood well enough to feed the dispatching algorithm. However having detailed passenger requests data for each journey, working at a low level (2.5 minutes interval or lower) and then, processing the results to obtain the desired five minutes forecasted data can be a useful approach.

The combination of more than one method has also been applied as a powerful approach, combining the better of the two methods to improve prediction accuracy.

The forecasting process must be evaluated in order to select the appropriate method. For this task, some indicators are needed to measure the quality of the method. In time series theory, three measures of the error are commonly used; MSE (mean square error), MRE (mean relative error) and MAE (mean absolute error). All of them calculate a discrepancy between the real data and the forecasted data. The equations 1, 2 and 3 show how these discrepancies are calculated. In all the equations, predictions are converted to OD matrixes, where OD_{ij}, represents the real OD matrix data for the origin-destination pairs, represented by (i, j). In the same way, ODe_{ij} is the estimated data matrix and f represents the number of floors.

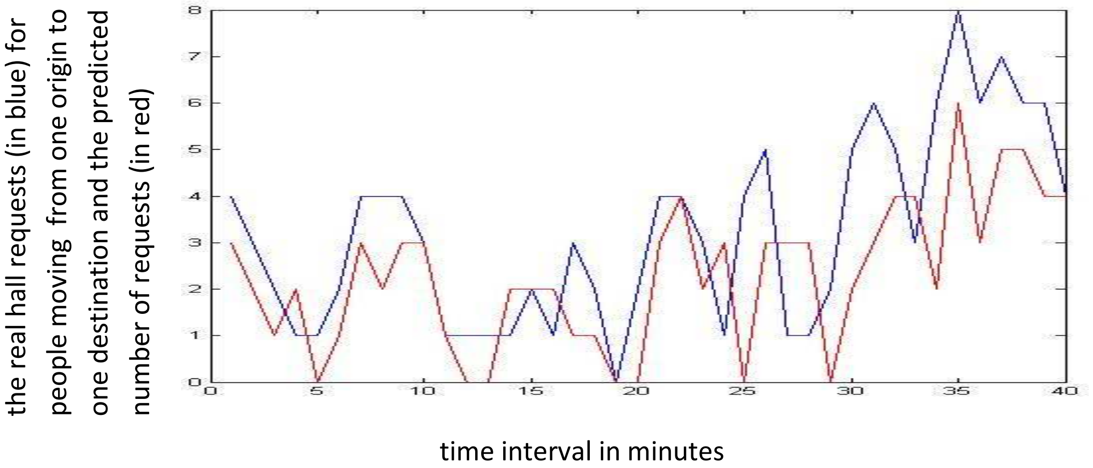


Figure 6: Passenger requests from one origin to one destination floor and the predicted requests

The first measurement is the mean square error (MSE) that describes the concentration and degree of dispersion about the error dispersion:

$$MSE = \frac{1}{2*f}\sum_{i=1,j=1}^{f,f}(OD_{ij} - ODe_{ij})^2 \tag{1}$$

The second measurement is the mean relative error (MRE), an indicator to evaluate the whole forecasting process:

$$MRE = \frac{1}{2*f}\sum_{i=1,j=1}^{f,f}\left|\frac{OD_{ij}-ODe_{ij}}{OD_{ij}}\right| \tag{2}$$

And the third measurement is the mean absolute error (MAE), the absolute average error between the predicted and actual values:

$$MAE = \frac{1}{2*f}\sum_{i=1,j=1}^{f,f}\left|OD_{ij} - ODe_{ij}\right| \tag{3}$$

Table 2 shows the results of the three error measurements for 14 intervals. They correspond to the time period between 11:40 and 12:45. The table shows the time period, the total number of real calls for this period and the total number of predicted calls. It shows also MSE, MRE and MAE. The table also contains prediction measurements, when data about the journey for each 2.5 minutes is used to feed the neural network. The results obtained are later used to calculate the mean for the number of requests coming for each origin destination. The results are really good with this second approach. We understand that the mean calculation process can reduce the impact coming from the great variability of this data.

Table 2 : Results for the prediction step for 5 minutes interval data.

		5 minutes time interval OD matrix based prediction				2.5 minutes time interval Od matrix based prediction			
Periods	Real calls	Estimated calls	MSE	MRE	MAE	Estimated calls	MSE	MRE	MAE
11:40-11:45	35	58	3,0682	67,42%	0,0523	34	0,5019	34,47%	0,0374
11:45-11:50	31	49	1,6970	54,55%	0,0302	32	0,3655	28,41%	0,0163
11:50-11:55	32	71	2,5076	73,48%	0,0500	43	0,4754	30,68%	0,0208
11:55-12:00	33	59	2,2424	65,15%	0,0560	44	0,4318	28,79%	0,0278
12:00-12:05	28	52	2,2727	62,12%	0,0501	50	0,6155	26,14%	0,0316
12:05-12:10	47	55	3,0606	68,18%	0,0710	47	0,6023	35,61%	0,0420
12:10-12:15	32	38	0,9242	34,85%	0,0217	40	0,3902	23,48%	0,0222
12:15-12:20	52	79	1,9167	53,79%	0,0490	52	0,5095	26,14%	0,0272
12:20-12:25	48	62	1,4848	53,03%	0,0469	40	0,9811	31,82%	0,0383
12:25-12:30	50	35	2,1894	67,42%	0,0489	48	0,6117	32,2%	0,0309
12:30-12:35	72	84	2,7576	72,73%	0,0510	64	1,1420	39,02%	0,0252
12:35-12:40	50	48	1,5303	57,58%	0,0624	54	0,4242	28,03%	0,0300
12:40-12:45	58	50	2,8485	69,7%	0,0883	49	0,4337	26,89%	0,0335
12:45-12:50	79	42	3,1288	79,55%	0,0586	57	0,9905	40,53%	0,0243
Total	647	782	31,6288	8,7955	0,7364	654	8,4753	4,3221	0,4075

CONCLUSIONS

In the vertical transportation the information provided by the log of the requests and trips of the cabs, provides the possibility to perform a comprehensive movement counting between floors. This valuable information can also be used to forecast demand in the minutes after. This will allow for better planning in dispatching and also support building applications that can take advantage of it. As for the prediction, neural networks offer good fitting to variable data. The methodology for analysis at high resolution and subsequent average at lower resolution has proven effective for this type of data but subsequent tests need to confirm it. Further development will consider origin-destination matrices estimation [2] and hybrid methods [7].

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