A Machine Learning Approach for Coordinated Voltage and Reactive Power Control

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ABSTRACT

Increasing penetration of renewable-based distributed generators (DGs) has transformed passive distribution networks to active distribution networks (ADNs). Therefore, traditional practices for voltage and reactive power (V/Q) control should be revised and improved. All control resources should be coordinated based on real-time information and in closed loop. To achieve this, machine learning (ML) is used to assist in making decisions by mapping the relationship between the selected network information and the desired control output. In this paper, setting of the shunt compensator operating in capacitive or inductive modes is coordinated with the tap position of the substation transformer such that all security measures are within the limits. Dataset emulating network behaviour during a year of operation is constructed for training a ML algorithm. A multi-class classification problem is formulated. Simulation results show satisfactory accuracy for some classes.

Keywords: Voltage and Reactive Power Control, Active Distribution Network, Feature Selection, Machine Learning

1. INTRODUCTION

Renewable energy sources (RESs) have played a significant role in modern power systems as an alternative to fossil-fuel generating units. Thanks to technological advancement and economy of scales, RESs can be installed in every part of the system including distribution networks at both medium- voltage (MV) and low-voltage (LV) levels in the form of distributed generators (DGs). Such interconnections inevitably change power flow patterns. Traditionally power in distribution networks flows in a single direction from the transmission system to loads. With DG connected, the power flow pattern in the network changes, and the operation is gradually transformed to active distribution networks (ADNs). Moreover, with greater penetration of RESs there is a great chance that the system would encounter some technical problems such as voltage rise, reverse power flow or mis-operation of protective devices [1]. Voltage and reactive power (V/Q) control has become a more important tool in maintaining integrity and security of MV distribution systems. This is due to existence of coupling between reactive power and voltage in MV levels while such relationship is not valid in LV levels.

The security measures, namely voltage and line flow violations, can be mitigated by adjusting reactive compesating devices. These may include network equipment such as on-load tap changer (OLTC) located at the substation, shunt capacitors (SCs) or tie switches. Moreover, it is possible to schedule the setpoint of DGs. This option is technically possible but provision to remunerate for ancillary service of the participating DGs is generally required. In classical control schemes, the setpoint of OLTC, SCs and tie switches are pre-determined based on historical data and rarely adjusted over the course of actual operation. To achieve better control performance and to accommodate high fluctuation of REs and loads in ADNs, the distribution system operator (DSO) needs better both centralized and decentralized control schemes.

In the present day, real-time monitoring and control for ADNs has become more technically viable and economically feasible due to advanced communication infrastructures, fast computing resources and large data storage. Moreover, research on soft computing has been quite well developed for the past two decades. Researchers have applied various techniques in soft computing to reactive power control for ADNs such as machine learning (ML) (i.e. neural networks [5]), fuzzy logic [2] or evolutionary computation (i.e. evolutionary algorithm [3], genetic algorithm [4]).

In the author's view, these applications can be broadly categorized into two groups namely offline planning and online control. The objective of the former is to determine the optimal control setpoint that will not result in any constraint violations. This is normally carried out offline based on the complete information of network data, forecast of loads and RESs. Simulation time is usually not of primary con-

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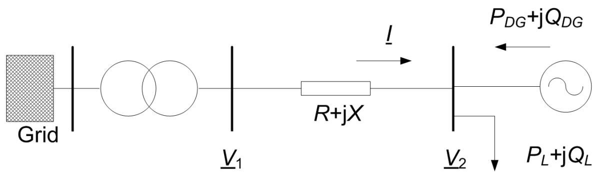

Fig.1: *A simple radial system.*

cern. On the other hand, online control is carried in closed loop and requires fast computing. The objective of an online approach is to find the recourse of control setpoint in order to eliminate violation of security constraints. Selected system variables are gathered and used as input for the tool. This paper pursues the second group of methods. The role of feature selection techniques in improvement of the classification accuracy is investigated. A method for generating the dataset to be served as the knowledge for learning of ML is presented. Two ML algorithms with different settings are chosen for testing the proposed methodology.

The rest of this paper is organized as follows. Section 2 discusses the basic principles of V/Q control in distribution networks and a framework for coordinated control in an example network. Section 3 presents the method for preparing input data for ML and the test distribution system. Section 4 discusses components of the developed ML approach, and gives the list of all possible input features. The feature selection methods and the potential scheme for real implementation are also discussed in this section. Section 5 discusses the simulation results. The paper is concluded, and the future outlooks are given in Section 6.

2. VOLTAGE AND REACTIVE POWER CONTROL

2.1 Overview

A simple MV radial distribution system is shown in Fig. 1 [1] with the line parameter $R+jX$, the complex power injected by DG denoted by $P_{DG}+jQ_{DG}$ and the complex load power P_L+jQ_L. Considering the power balance at Bus 2 and assuming that DG does not inject active power to the network, the magnitude of current flowing from the grid to the load is

$$I = \frac{\sqrt{P_L^2 + (Q_L - Q_{DG})^2}}{V_2} \tag{1}$$

It can be observed that the current can be reduced by reactive power compensation, i.e. Q_{DG} in this case. Knowing the current, voltage drop across the feeder is defined by

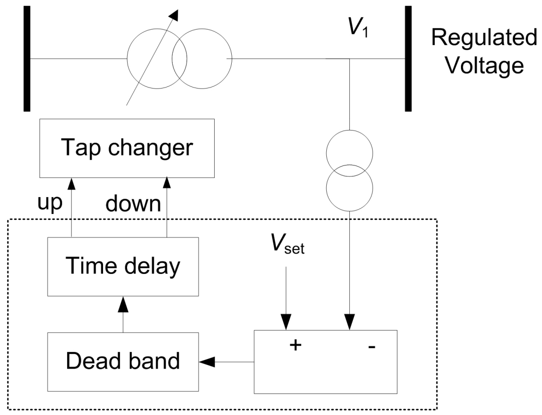

Fig.2: *Classical control of OLTC.*

$$\begin{aligned}\Delta V = IZ &= \frac{\sqrt{(P_L^2 + (Q_L - Q_{DG})^2)\,(R^2+X^2)}}{V_2} \\ &\approx \frac{RP_L + X(Q_L - Q_{DG})}{V_2}\end{aligned} \tag{2}$$

It can be observed that the voltage drop can be controlled by reactive power. For example, if DG injects reactive power ($Q_{DG} > 0$) voltage drop ΔV decreases. Notice that the grid voltage V_1 is almost unchanged, then the voltage at Bus 2 increases. However, grid codes of many utilities require DG to be controlled at unity power factor, any shunt compensating devices connected to the PCC will have the same impact to the voltage but with slower response and coarser adjustment. Moreover, DG with much faster response could be present in reactive power. This depends on the grid code of the network operator.

The power transformer located at the substation is typically equipped with an on-load tap changer (OLTC). The control scheme of the OLTC is shown in Fig. 2.

The control objective is to regulate the secondary bus voltage of the substation V_1 within the upper and lower bounds. Alternatively, another regulated bus such as the far-end bus can also be selected. The difference between V_1 and the setpoint voltage V_{set} is computed and checked to see if such difference is outside the dead band for a pre-specified duration given by the time delay. The control signal will be sent to adjust the transformer either up or down. Therefore, OLTC is a slow control with global impact to all buses connected to that substation. Moreover, movement of OLTC should not be very frequent due to operation and maintenance (O&M) costs and lifetime.

Shunt compensators including capacitor and reactor is a common element in distribution networks. The working principle of these devices is like that of OLTC. The voltage, i.e. feeder voltage is measured and compared with the control setpoint. Then, the

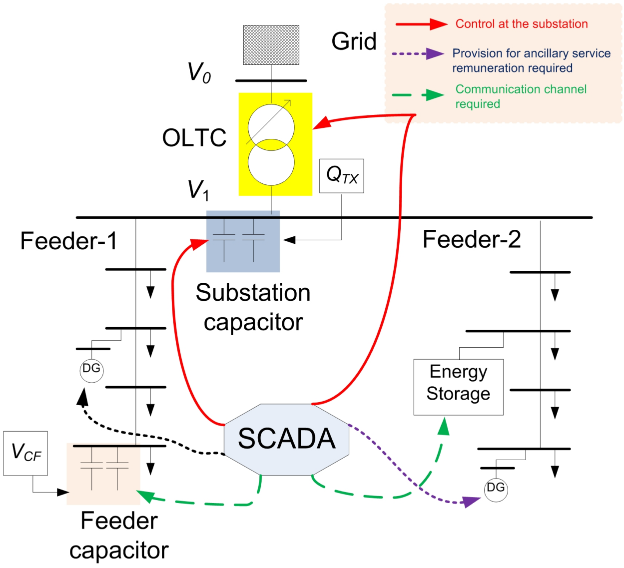

Fig.3: *Coordinated control scheme (adapted from [8]).*

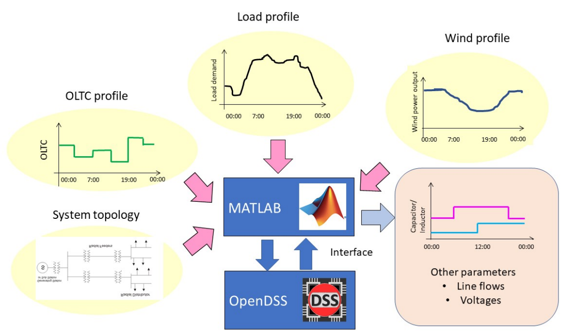

Fig.4: *Framework for producing the dataset.*

controller sets an appropriate level of compensation in discrete steps.

2.2 Coordinated control scheme

Fig. 3 shows an example of coordinated V/Q control for ADNs. The control resources available here are OLTC, shunt capacitor at the substation C_S, shunt capacitor at the feeder C_F, energy storage and DG control setpoints. For OLTC, the substation voltage V_1 is the control target. By adjusting the tap, reactive power flowing over the transformer Q_{TX} changes. This would affect loadability of the transformer. The capacitor C_S is used to compensate Q_{TX} and allows the transformer to carry more load. The feeder capacitor C_F is used to control the voltage of the bus to which it is connected, namely V_{CF}. Note that capacitor switching changes the reactive power flow in the network. Theoretically, all DGs in the system could participate in V/Q control. However, the provision of ancillary service is required, and this is beyond the scope of this study. Since this example is a centralized scheme, communication channels for telemetry and sending control commands are required. Power electronics-based energy storage can be also controlled to supply reactive power in addition to supplying the stored energy surplus.

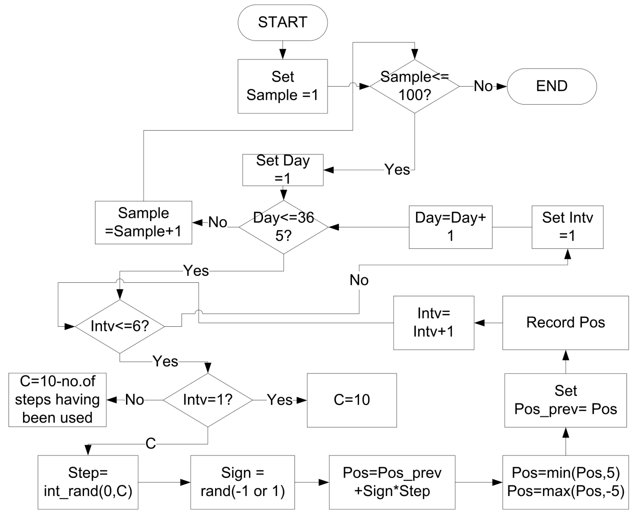

Fig.5: *Process for generating yearly profiles of OLTC.*

3. GENERATION OF DATASET

3.1 Overview

To develop an online control scheme, the dataset is needed to serve as knowledge for machine learning. This dataset could come from historical data or simulation studies. This paper adopts the latter direction.

Fig. 4 shows the conceptual framework for producing the dataset. The simulation is carried out in a MATLAB-M file receiving inputs consisting of yearly load profile and yearly wind power profile, system information and the simulated OLTC movement in the year. The change of tap position in a day is capped to the pre-defined limit like in [6]. The 'OpenDSS' software package [11] is used for network simulations and the interface with MATLAB is developed to retrieve all results. The shunt capacitor and shunt reactor are adjusted in steps such that all bus voltages and line flows are within the allowable limits. If the voltage of the controlled bus is above the limit, the shunt reactor sequentially increases the control step to absorb reactive power until the voltage is below the limit. On the other hand, if voltage of the controlled bus is below the limit, shunt capacitor is responsible for compensating reactive power until the under-voltage is eliminated. By this control logic, OLTC and shunt compensators are coordinated based on real-time measurements.

3.2 Input yearly profiles

The yearly profiles used for the simulations in this paper consist of OLTC, load and wind power. As

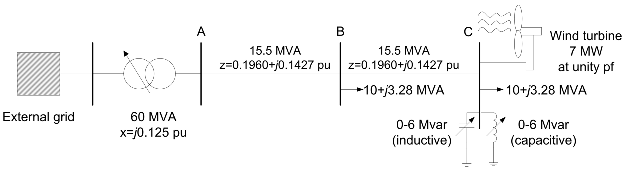

Fig.6: *Test MV-distribution system.*

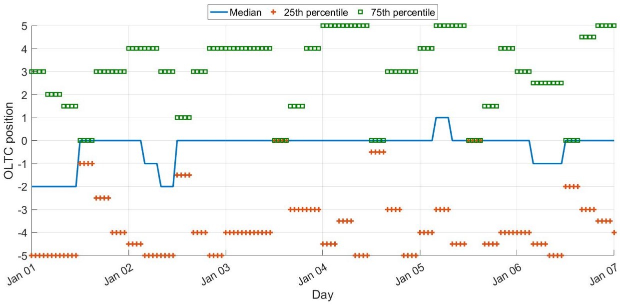

Fig.7: *Statistics of the random profiles of OLTC in 7 days.*

mentioned earlier that OLTC has global impact to all downstream buses and has slow response, the tap position is fixed during the duration of 4 hours. This means that OLTC can changes the tap 6 times in a day at maximum. The procedure for generating OLTC profiles is shown in Fig. 5.

A sample represents the hourly movement of OLTC throughout the year. The maximum number of samples (‘Sample’) in this simulation is set to be 100. Power flow is sequentially run for each hour of the day (‘Day’). Each day is divided into 6 intervals (‘Intv’) with equal time step of 4 hours. For the first interval, the size of step change C is set to the maximum number (i.e. fixed to 10 for this case). For the rest of the intervals, C is defined by the difference between 10 and the number of steps that has been already used in the day. By this logic, the maximum number of tap changes is limited to 10 steps per day. Then, the step change (‘Step’) is randomly generated as an integer between 0 and C. The direction of change to either increase or decrease is given by the variable ‘Sign’ that has a random value either -1 or 1. Thereafter, the tap position ‘Pos’ is updated from the one of the previous interval namely ‘Pos_prev’ and then checked to see if the updated value is within the upper bound (i.e. 5) and the lower bound (i.e. -5). The new value of ‘Pos’ is recorded and set as the ‘Pos_prev’ in preparation for the updating process of the next time interval. The procedure discussed earlier is repeated until the last interval is reached. Then, the counter ‘Day’ is increased and the counter ‘Intv’ is reset to 1. The entire procedure is terminated when the last ‘Sample’ is produced.

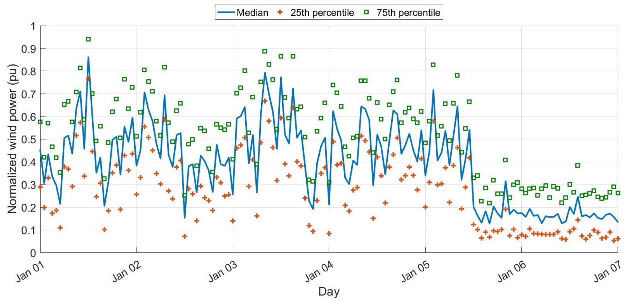

Fig.8: *Statistics of the random profiles of the normalized wind power in 7 days.*

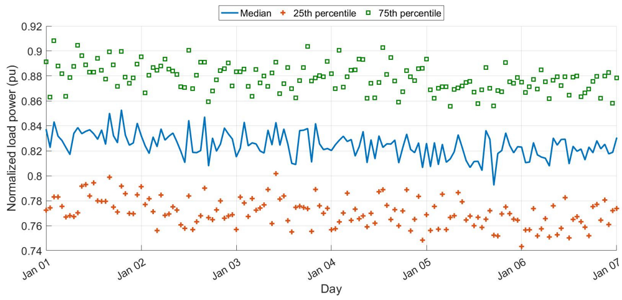

Fig.9: *Statistics of the random profiles of the normalized load power in 7 days.*

3.3 Test system

The effectiveness of the proposed method is verified by simulation on a medium-voltage (MV) distribution test system modified from [13] as shown in Fig. 6. The two feeders are assumed to be identical. The parameters of feeders and transformer are given in per-unit based on the their own ratings. The security limits to be enforced in this study consist of:

- voltage level of all buses to be within $\pm 5\%$ and
- apparent power flow below the line capacity 15.5 MVA.

To achieve that, two shunt compensators with 6 Mvar (both capacitive and inductive each) are installed at Bus C in which a 7-MW wind turbine controlled at unity power factor is connected. This wind turbine is assumed to have no provision for reactive power ancillary services.

4. DEVELOPING MACHINE LEARNING

4.1 Statistical properties of dataset

The 100 samples of the first week are extracted and the mean and 25^{th} and 75^{th} percentiles are computed as shown in Fig. 7. This is obvious that the samples are centered around the nominal position with variation within the pre-specified bounds.

For wind [9] and load [10] profiles, the public data of a German TSO namely 50 Hz in the year 2017 with the time step of 15 minutes are taken as the base. Then, hourly average is computed and normalized. The normalized profile is used as the mean and

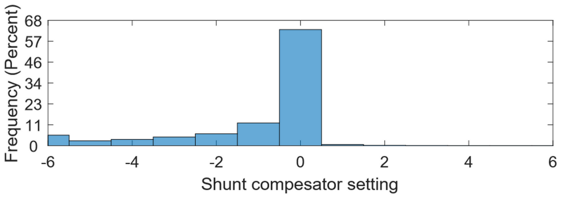

Fig.10: *Distribution of shunt compensator settings.*

Table 1: *List of input features.*

Feature no.	Symbol	Description
1	P_w	Wind power injected to bus C
2	P_d	Total power demand
3	a	Transformer tap position
4	V_s	Voltage at point of connection to the external grid
5	V_A	Voltage at bus A
6	V_B	Voltage at bus B
7	V_C	Voltage at bus C
8	S_{A-B}	Apparent power flow over line A–B
9	S_{B-C}	Apparent power flow over line B–C

with the pre-defined level of variation, new random samples are generated. The statistics of normalized wind power and load power based on 100 samples of the first week are shown in Figs. 8 and 9, respectively.

Fig. 10 shows the distribution of the shunt compensator settings that are generated from the procedure described in Section 3.2. It is obvious that almost 60% of the operating conditions do not need reactive compensation while those that do required capacitive compensation. Moreover, there are very few instances of operating conditions needing to absorb reactive power.

4.2 Input features

The list of nine potential features that can be retrieved from the test system shown in Fig. 6 is given in Table 1.

The features can be categorized in three main groups namely power consisting of Features 1-2 and 8-9; voltages consisting of Features 4-7 and tap position (Feature 9).

4.3 Feature selection

The number of input features depends on the size of the distribution network. In most cases, the complete set of information is simply too large for any machine to effectively learn the underlying pattern. Therefore, the number of input features should be reduced before passing on to the machine learning algorithm to improve generalization capability and to reduce learning efforts. This process is called dimensionality reduction that can be broadly categorized into two groups namely feature selection and feature extraction. In feature selection, a subset of the original feature set is selected to represent the characteristic of the full set of features whereby the original feature set is transformed and selected to a reduced and new feature set in feature extraction. In this paper, the impact of feature selection on the classification accuracy is investigated. Therefore, feature extraction such as principal component analysis (PCA) is not considered.

Table 2: *Score ranking given by selected feature selection techniques.*

inf-FS 2016	ECFS	mutInfFS	MCFS	Fisher	CFS	Lasso
3	3	3	6	8	2	8
8	8	8	7	7	3	9
7	7	7	8	6	1	1
6	6	6	5	4	9	3
4	4	5	9	5	8	4
9	9	4	4	9	4	6
5	5	9	3	3	7	7
2	2	1	1	2	5	2
1	1	2	2	1	6	5

Seven feature selection techniques that have been widely used in related research communities are adopted [14]. These consist of INfinite Feature-Feature Selection updated version in 2016 (INF-FS 2016), Eigenvector Centrality Feature Selection (ECFS), Mutual Infinite Feature Selection (mutInfFS), Unsupervised feature selection for multi-cluster data (MCFS), Fisher discriminant (Fisher), Correlation based feature selection (CFS), Feature selection through regularization (Lasso). The score rankings given by the selected techniques are given in Table 2.

The number given in the table represents the feature number. For each selection technique, features are ranked based on the score. The feature in the first row is the best feature. The first five features having been selected by most of these seven techniques are chosen. The set of features being selected include Feature Numbers 3, 4, 6, 7, 8. The effectiveness of ML using the selected features is verified with two cases namely all features and features based on heuristic rules based on experience of the network operator.

4.4 Conceptual design for real implementation

Based on the proposed methodology and the results from selected feature selection techniques, a conceptual scheme in which machine learning (ML) to be implemented in the real world can be shown in Fig. 11. The required measuring quantities consist of voltages from three locations namely external grid, Buses B and C, apparent power flow (absolute of the

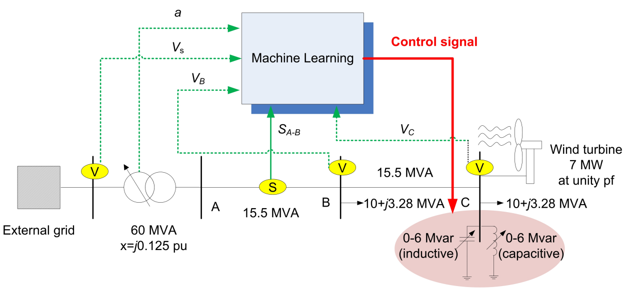

Fig. 11: *The conceptual design for real implementation.*

maximum in both directions) over line A–B and the transformer tap position. These five quantities are fed to the ML trained offline in order to give the control signal for the suitable setting of the shunt compensator. Therefore, this control signal is a discrete variable between –6 to 6. The negative values between –6 to –1 represent supplying 1 to 6 Mvar by the capacitor. On the other hand, the positive value between 1 to 6 represent absorbing 1 to 6 Mvar by the reactor. The value of zero shows the situation where reactive compensation is not required.

4.5 Machine learning

Machine learning (ML) is a component of soft computing that has been used in many real-world applications. The working principle of ML relies on algorithmic and statistical models to perform a specific task without having explicit instructions provided by the user. A mathematical model is constructed based on the knowledge gained through learning from data. Supervised learning is generally used to train the ML engine to build the relationship between the collected inputs and the desired outputs. Classification is one of the tasks which ML has shown great capability to deal with. In this paper, two groups of ML techniques that can be easily trained are chosen namely classification tree and k-nearest neighbors (KNN) algorithms. The 'Classification Learner' app in MATLAB [12] is used for verification of the proposed methodology.

5. SIMULATION RESUTLS

To demonstrate the impact of feature selection on the classification accuracy, two methods for handling input features are considered namely all inputs and heuristic. The former feeds all nine inputs to the ML during learning while the later uses heuristic rules for selection of five inputs. For the classification tree, three models based on complexity of the tree are used namely complex, medium and simple trees. For the KNN, various techniques namely fine, medium, coarse, cosine and weighted KNNs are considered. Table 3 shows accuracy of classification based on the use of different ML algorithms and different feature handling techniques. The results show that the medium tree and simple tree based on the selected input features are the most accurate. Confusion matrix of the simple tree method is shown in Fig. 12. All the classes '0' (no compensation required) are correctly predicted. The class '–6' (–6 Mvar from the capacitor) can be predicted with accuracy of 91%. The prediction accuracy of class '–1' is 75%. For the inductive zone, the prediction of class '1' is 93% accurate. The classes '2' to '6' are nearly impossible to be predicted due to unavailability of these classes in the training set. In the capacitive zone, the classes '–2' to '–5' cannot be predicted at all. One of the possible reasons is distribution of these classes are flat, making class separation in this region become extremely difficult.

Table 3: *Accuracy of classification based on different ML algorithms and feature handling techniques.*

ML Algorithm	Handling of input features		
	Selected inputs	All inputs	Heuristic
Complex tree	80%	79.8%	79.7%
Medium tree	80.2%	80%	79.8%
Simple tree	80.2%	80%	78.6%
Fine KNN	78.8%	74.1%	74.2%
Medium KNN	78.5%	76.9%	76.9%
Coarse KNN	79.1%	77.5%	76.8%
Cosine KNN	75.5%	74%	73.8%
Cubic KNN	78.4%	76.5%	76.7%
Weighted KNN	79.7%	76.6%	76.3%

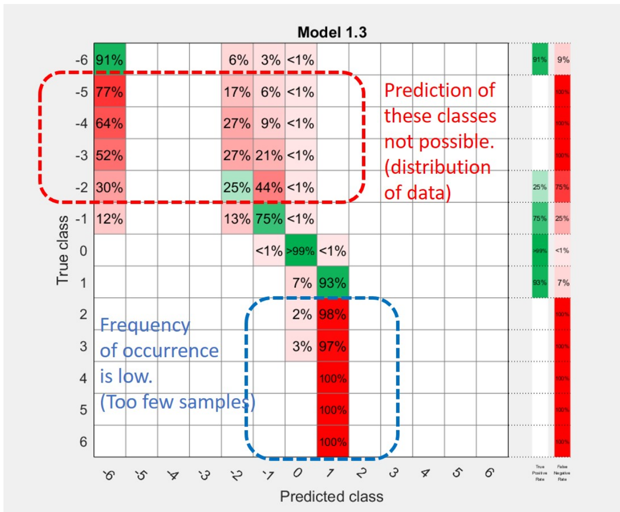

Fig. 12: *Confusion matrix of the classification.*

6. CONCLUSION AND FUTURE OUTLOOK

In this paper, a machine learning (ML)-based approach for voltage and reactive power (V/Q) control in an active distribution network is presented. A dataset emulating operational behavior of the network is constructed and used for training a ML algorithm. Modern feature selection techniques are applied to select five important features. Based on three methods for handling inputs and two MLs with different settings, the classification of simple-and medium-classification tree methods are the highest. The confusion matrix reveals that performance of the developed ML heavily relies on distribution of the target output and the number of samples in each class. Future research will focus on the strategy to improve the prediction accuracy and application to larger practical systems. In the cases of many renewable sources, the location of reactive power compensators should be determined from sensitivity analyses to ensure effective control results. Moreover, additional engineering judgement has to be applied to pre-screen the candidate input features before applying feature selection techniques.

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