BUSAN 302 A2

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Opening Remarks

As you read this report, you will find that, at parts, I have not strictly followed the order of the marking scheme. Parts of each chapter can be found sprinkled throughout the report. I have still labelled how it does loosely follow it to help serve as a guide. While I appreciate this will make my report more difficult to mark, I ask that you please bear with it.

Chapter 1

Drones NZ is a business founded upon its customers. Unlike other drone suppliers that ship generic ready-to-fly options, Drones NZ separates itself from the competition by including customers in its process. Drones NZ offers customized solutions for a large number of different purposes, which means that Drones NZ must consider countless variables to ensure customer satisfaction. Furthermore, the added dimension of after-sales support means that Drones NZ must maintain a constant channel between themselves and their customers to ensure the customer’s needs are met. The success of Drones NZ as a business critically depends on their customer’s level of satisfaction, as the lack thereof would severely undermine Drones NZ’s reputation as a custom-solution provider.

This leads into the problem facing Drones NZ. In order to ensure customer satisfaction, enormous amounts of data must be processed. Customer satisfaction is gauged via regular feedback from customers which arrives in text format. For the purpose of this assignment, we assume that the response rate is large enough to capture significant amounts of data that is representative of an accurate general consensus.

The Problem

Analysing customer feedback reveals that customer satisfaction is largely dependent on 3 variables – speed of after sales service, reliability of drone performance, as well as cost.

In other words, the problem facing Drones NZ is the struggle to maintain a high level of customer satisfaction.

This can be broken down into the following 3 sub-problems:

- Inability to rapidly adapt supply-chain in response to customer feedback.
- Inability to analyse large amounts of drone flight data.
- Inability to mitigate expert service costs.

A decision support system (DSS) will add significant value to the business as it will be able to constantly process customer feedback, along with information about business and drone performance to create insightful information regarding the operations of the business. This will help stakeholders make informed decisions.

The stakeholders can be broken down by type:

Primary	Secondary	Facilitator	Indirect
Executives	Customers Technicians Suppliers Contractors	Software and computer system engineers Information system architects	All other staff

In this case, we are interested mainly in the effect on primary and secondary stakeholders.

Primary stakeholders inherently absorb the bulk of the risk and reward associated with the implementation of the DSS. In the best case, primary stakeholders will be able to make fast, informed decisions on how their business performs but will be at risk of the system being potentially too slow to adapt to rapidly changing customer feedback, too complex to be able to maintain as the business changes, or even ineffective at improving customer satisfaction.

Secondary stakeholders will be those on the ‘front-line’ of the DSS. I.e. they will be affected the most significantly in their day-to-day operations. Should the DSS be highly effective (and utilised), secondary stakeholders (apart from customers) will have to make constant adjustments in their approach. For example, suppose the DSS identifies that customer sentiment is negative due to shipping delays in goods from China. In that case, it may recommend in sourcing goods from Germany instead. Naturally, this will affect the order-book of the suppliers.

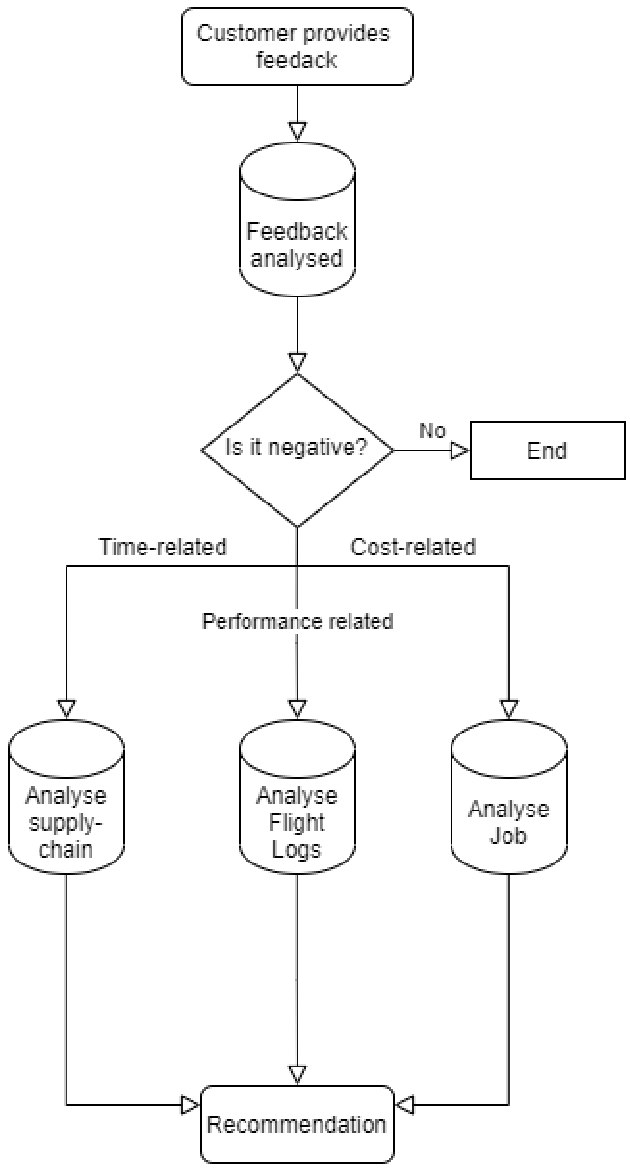
KPIs will be can be generated per business requirements from the dimensions covered by the DSS. In theory, the DSS will integrate all current data collected by the business, so the number of dimensions to consider will be extensive.

Some key KPIs that will reflect on the performance of the DSS in relation to the business problems could include:

- Change in customer satisfaction over a period of time
- Change in cost-related satisfaction per number of in-house experts
- Decrease in customer-issue related expenses over a period of time

Chapter 2+3

The use of ML algorithms for the identified sub-problems will be significantly more effective than employing human interpreters for customer feedback. The nature of such algorithms means that large amounts of customer feedback can be automatically processed and used as input data for other algorithms. Continuously evaluating customer sentiment by manually processing feedback data would prove to be not only arduous and time-consuming, but expensive too. Furthermore, sentiment data would need to be transformed and loaded into an algorithm processable form by human operators. ML algorithms can then be applied for solving the problems identified from the customer sentiment analysis. ML algorithms will be more effective at identifying congested supplied networks by constantly comparing their state to historical data. They will be able to analyse enormous amounts of drone flight data and compare it to model behaviour, as well as serve to replace out-sourced expert services by providing troubleshooting themselves. The scope would be large with separate algorithms for different problems, as seen overleaf. This is a early stage overview of how such a DSS may look like.



The requirements for the DSS can be interpreted from the type of data the system will receive, and the type of data that is desired from the system.

To analyse customer feedback, an algorithm capable of analysing and interpreting natural language is required. A text-mining algorithm will perform discovery-driven data mining, utilising natural language processing and ultimately it will undertake a sentiment analysis. In its process it will eliminate frequently used stop-words, replace remaining words with their stems and calculate weights of remaining terms. After this, the text mining algorithm will use clustering to associate a particular sentiment and cause with each unit of feedback. It should achieve a relatively high level of accuracy, tolerance for complexity and noise in data as its purpose is to make sense of the ‘noise’. It is also inherently scalable - input only comes from a single source and as it grows it is simply more noise for the algorithm to process.

The output in the end will enter a data warehouse where it will be able to integrate with existing records. For example, the algorithm determines that a customer had a poor experience with a service job. This would be stored in the data warehouse with a uniquely identifying key (e.g. Feedback_ID) and has foreign keys linking to the corresponding service job and customer. The algorithm can then utilize these records, analysing the supply chain to determine whether the feedback is associated with shipping delays, cancellations, etc.

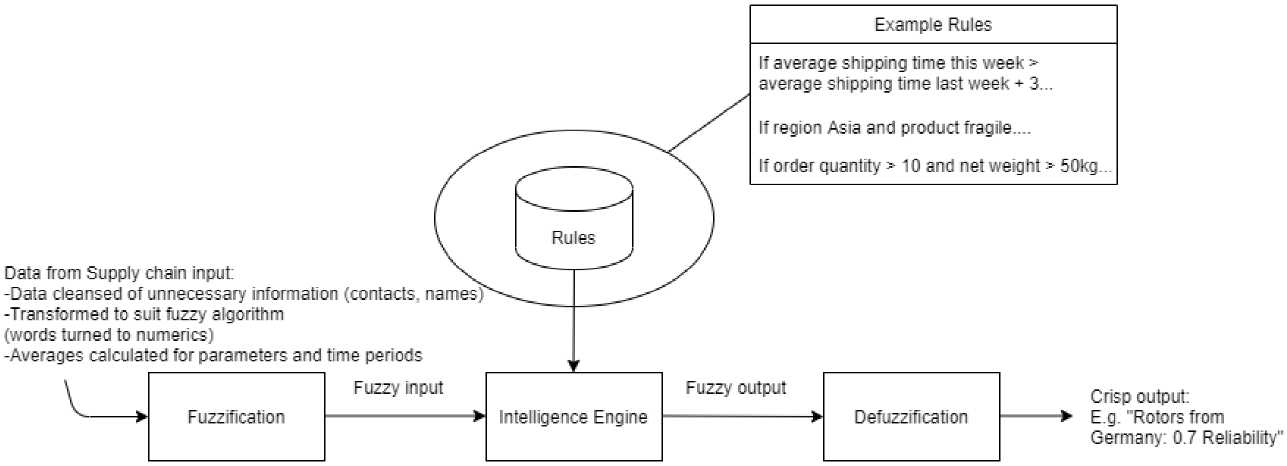
Text-mining was selected as the ideal algorithm for analysing customer feedback as it is capable of analysing large volumes of non-structured text. An algorithm needs to be able to analyse non-structured text in particular, as this provides the opportunity for customers to provide feedback in the most candid manner. A discovery-driven model is selected such as not to inflict bias upon the customer feedback data.

Ultimately, the text mining algorithm will produce some result that will need acting upon. One potential output is that it has detected an uptick in negative customer feedback from customers having just completed service jobs that involved replacing a rotor.

<u>Supply Chain Issues</u>

Here, a DSS system with fuzzy logic can be used.

Fuzzy logic proves to be ideal in this scenario thanks to its reasonably high level of accuracy, tolerance of complexity and flexibility, over a rule-based system which may have difficulty scaling due to its demand for system resources and inability to consider subtle nuances in data. For example: Drones NZ maintains a constant connection with its network of suppliers. Relative to past performance, a particular supplier’s goods have been taking longer to arrive. Additionally, more fragile goods are more likely to arrive broken from one supplier than another. While goods from another region are being lost in transit entirely. A fuzzy logic system will be able to analyse all this data and provide a score for each good, with the ability to drill-up and produce scores for countries and regions. It will be able to suggest a substitute for the supplier, for example that carries less risk but longer shipping time (determined by the fuzzy scores). A rule-based system will offer a black-and-white interpretation of the supply-chain which may not be as useful in decision making where compromises may need to be made.



An example of how the fuzzy logic model may be implemented

A downside to using fuzzy logic, however, would be the calibration of rules in its implementation. Rule designers would need to study past supply chain data to determine what factors determine shipping time and reliability as well as how each strongly each particular factor contributes to the final outcome, this may take several iterations before a reliable set can be settled on. Additionally, due to the unpredictable nature of the universe, sometimes the fuzzy score may not be a completely accurate representation of a particular order.

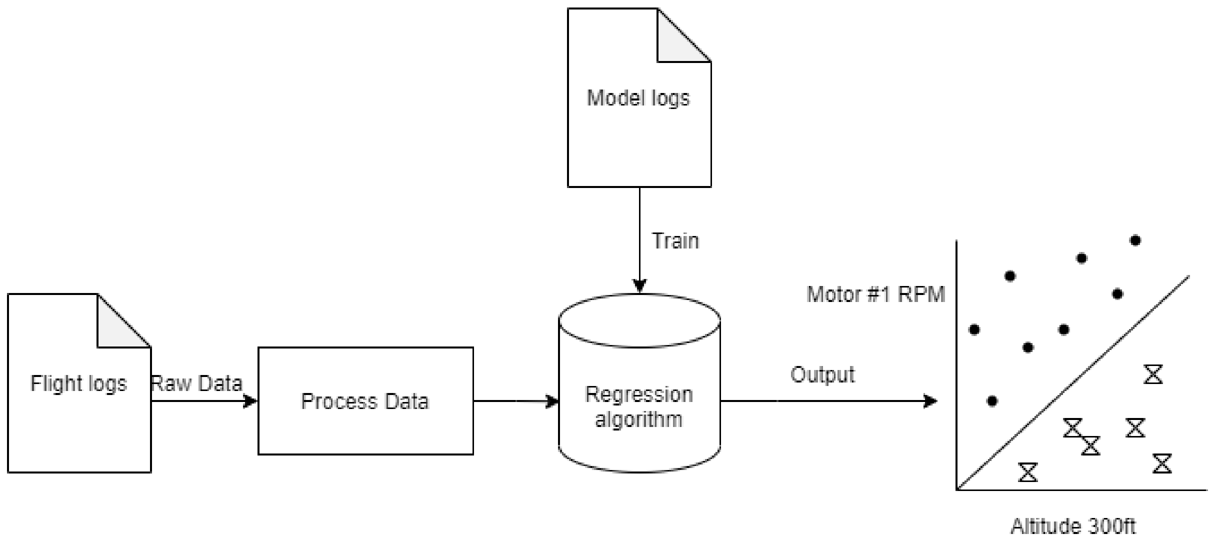
Ultimately, however, fuzzy logic will increase the intelligence density of supply-chain data by incorporating supply-chain wide information into one compact figure. Executives can then make a decision based on this number, thus, solving the supply chain problem.

<u>Drone Performance Issues</u>

Autonomous drone flight involves highly complex algorithms and magnitudes of data. While it should be extremely reliable in theory, there may be bugs, edge-cases, and other unforeseen elements that appear during widespread user adoption. It is critical for Drones NZ to be able to quickly respond to reported issues by analysing drone data and comparing it to the designed flight models.

Due to the magnitude of data to comb through, it is unfeasible for a human operator to perform much of the data analysis (a human could review highlighted problem areas, though). Subsequently, a ML algorithm must be selected that is capable of processing such data. In this scenario, a large amount of drone flight data is collected from the drone's various sensors. To be able to determine what the issue is, Drones NZ must be able to compare the expected data to the actual data. One way to obtain the expected data is by performing a regression analysis to predict the numerical values based on existing models. We assume that Drones NZ already has models for a multitude of different scenarios such that the regression algorithm can be learned by supervision. Regression analysis works better for this task over other algorithms due to its ability to correlate data with existing data (and subsequently make it clear where unexpected data is occurring). A similar type of predictive algorithm like clustering is not helpful in this scenario as grouping drone performance data would not be of particular use to Drones NZ and although the technician is effectively making a decision based on a numeric input, a decision tree is too simple and would not be able to provide insight into large amounts of data (readings from drone sensors could be taken as frequently as several times per second). Supervised regression analysis is not the most flexible of algorithms as it depends on the provided training data to make any amendments to the model. Subsequently if maintenance is to be performed it does require the potentially costly intervention from experts. However, once a model is created for a particular drone model, it will not require maintenance as long as the drone does not change, but, a technician will need to review the produced results to identify problems with the drone according to the expected performance versus the actual performance.

Implementation of the regressive analysis algorithm will involve sourcing flight data from the customer's drone. We assume that as part of the feedback, the customer uploads a log file with all of the drone's operational details recorded in text form. The text is logically categorised for each of the drone's parameters e.g. a column for rotor data, proximity data, location data etc. This data is inputted into the regressive analysis algorithm that has been trained on flight data from the same model of drone. As it processes the data, it compares data that the drone has control over such as its rotor RPM on the Y-axis (as the dependent variable) and environmental data such as altitude or windspeed on the X-axis (as the independent variable). The algorithm then analyses how the environmental data affects the drone data and how it differs to what is expected based on the model. If it detects significantly different data that correlates to specific environmental circumstances it will display this in the form of an abnormal line drawn through the plotted points. It is important that the algorithm is not over-trained to its model data as this may result in frequent 'false-positives' from the customer's drone data just as a result from natural variation in performance.



How the system may be implemented

Using this insight, the technician will be able to determine what set of circumstances is causing the drone to malfunction in real-world usage and implement a fix, thus, solving this problem and increasing customer satisfaction.

<u>Excessive Service Costs</u>

Unlike the previous sub-problems, this can be implemented before 'issues' are discovered, and negative feedback pointing towards high service costs can serve as an opportunity to look into why technicians are contacting experts and whether the ML algorithm is functioning properly or needs refinement.

At the current point in time, technicians resort to expensive expert support to guide how to proceed with drone service. This problem lends itself nicely to ML algorithms. Troubleshooting is defined on Wikipedia as "a logical, systematic search for the source of a problem to solve it" thus, it can inherently be accomplished by a machine as there is a finite number of paths a human expert can take, each with well-defined decision points. Therefore, a decision tree naturally fits the requirements of this problem. A decision tree is effective at answering binary questions and providing a result based on their answers. This would be of particular use to Drones NZ technicians as they would be able to interface with the algorithm by inputting drone problems, and it will output the necessary actions required by the technician. A decision tree fits this problem best due to how closely it fits the troubleshooting process of a human and how easy it is to use. Technicians will be able to immediately take advantage of quick expert guidance without a significant learning curve. Other algorithms are geared to much larger and less understood quantities of data, making them less suited to this problem. Additionally, they would be much more difficult for technicians to quickly use in their day-to-day operations. However, the point of most concern here is obtaining the information necessary to train the decision tree in the first place. Asking the support provider for it would be contrary to their bottom line. Hence, Drones NZ could approach teaching it in a few different ways. Drones NZ could either make a deal to purchase service information from their current provider for some fee or Drones NZ could log ongoing service data until the vast majority of drone issues have been recorded. The latter would mean that the decision tree's implementation would be delayed and may not cover all service requirements as infrequent issues may not have been recorded during the data collection period. It would, however, be unrealistic to try to train the algorithm without any reference data, subsequently the business will be required to decide on which option would best fit their needs.

To use the decision tree, technicians would load drone performance data using a simple, user-friendly user interface. It's important to note at this point that the decision tree is incapable of providing guidance on matters regarding drone's autonomous flight performance. This is addressed in the previous algorithm. The decision tree can only direct technicians on how to proceed during the majority (or for how much it is trained) service jobs. A simplified example implementation of such a decision tree can be seen in the appendix (page 11).

Chapter 4

To reiterate, Drones NZ employs a unique business model that closely involves the customer, from the design, to after sales support. Drones NZ's business would suffer significantly from prolonged negative customer feedback. Subsequently, it is critical the Drones NZ can quickly adapt when the feedback is received.

The solution that is proposed involves reducing costs in drone servicing using a decision tree algorithm, as well as creating an interlinked decision support system to assist executives and designers in maintaining reliability from the supply chain to the drone's flight performance.

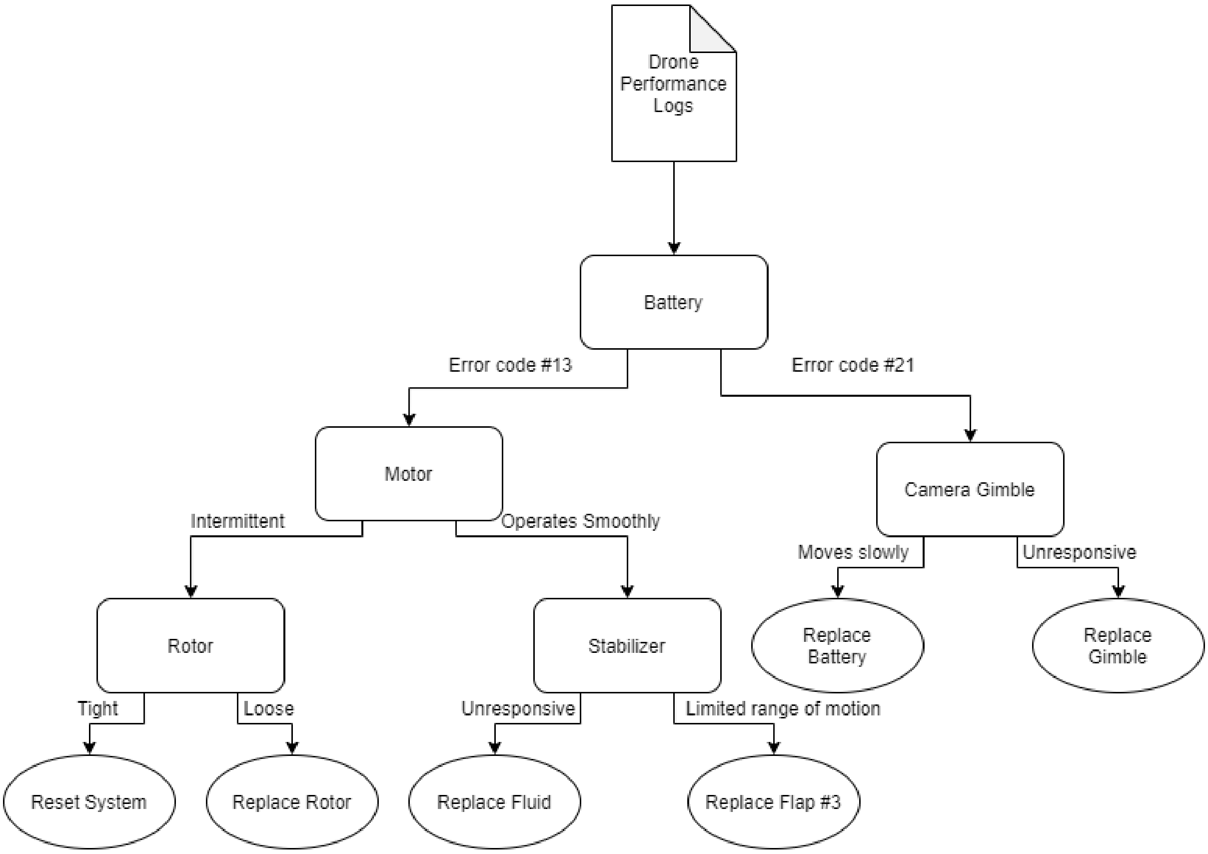
A conceptual diagram of the system is found in the appendix (page 12).

The solution analyses customer feedback using a text mining sentiment analysis, and automatically stores key information in an integrated with all other records. This information is then fed into different ML algorithms depending on was determined by the sentiment analysis. If the feedback is regarding time, a fuzzy logic algorithm analyses the state of the supply-chain and makes a recommendation to the executive based on its findings. If the feedback is regarding drone performance, a linear regression algorithm processes the drone's performance data and compares it to its model for that model of drone. Any abnormalities it finds are delivered to the designers to inspect closer. While if it is determined that customer feedback is regarding service cost, the executive is notified as it may mean the decision tree algorithm needs refinement.

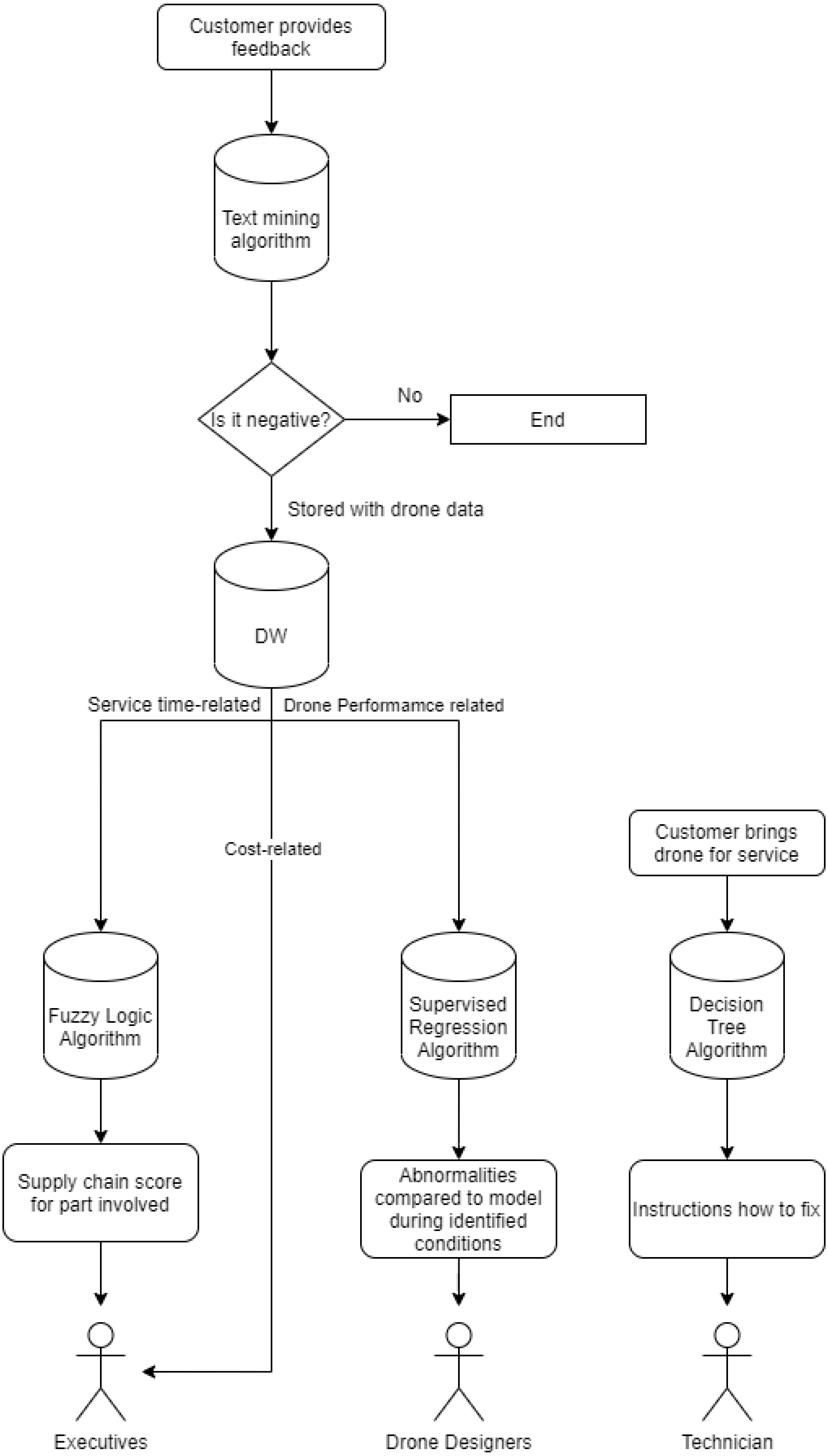
This solution significantly affects many stakeholders. Executives, technicians and customers will experience significant benefits, suppliers depending on the supply chain and contractors suffering due to the decision tree algorithm.

The solution may find its limitations when it comes to noise in data, unreliable data, or when certain edge cases crop up for which the algorithms are not designed to account for. Additionally, their implementation and maintenance requires a high level of skill and computing power, and in the end, they still require humans to make a comparison or take a closer look. Thus, they still ultimately rely on the imperfect human skill of reasoning.

Appendix



Example of a simplified implementation of a decision tree algorithm



A refined overview of the overall infrastructure

Jillian and James Ciao set up in business, in January 2020 selling customised drones to organisations and individuals. They named their business ***Drones New Zealand (Drones NZ)***. The purpose of the organisation is to customize sales of drones for a plethora of purposes that individuals and organisations use drones for in New Zealand and provide after sales maintenance. Examples of customers include: individuals and organisations in sports and recreation; restaurants delivering cooked food that must be kept warm or cold; shops, such as DIY stores delivering small items; farms and conservation groups for spraying fertilisers, weed-killers etc.; organizations taking aerial photographs of animals, pests, vegetations, etc.; and NGOs for delivering dry goods in disaster struck areas. ***Drones NZ*** not only sells drones but also provides after-sales service. There are many types of drones and the knowledge needed to service them is wide and varied. Expert knowledge is very expensive, and ***Drones NZ*** cannot afford to call experts each time a service needs to be done. A wide area of knowledge, both mechanical and IT-based, is needed because there are many different types of drones which uses different types of software. Hence, the knowledge required by maintenance engineers must span the range of products. The costs incurred in expert services are therefore also very high. Jillian who is a software engineer and James a mechanical engineer, have decided to utilize the capabilities of machine learning algorithms/data mining to solve this problem, of needing a wide variety of skills. Their immediate attention on this has an impact on other matters. These include, hiring staff, reducing expenses of consulting experts, and demanding and utilising service contracts for products bought from suppliers. ***Drones NZ*** stock drones and parts needed on a just-in-time basis, to reduce the amount spent holding stocks. They must have a network of suppliers and information about the products and services that the suppliers provide, such as costs of the various items and the average time taken for delivery. This information must be updated as changes happen (as information on price etc. may change frequently). Such changes when they happen must be communicated to ***Drones NZ*** by the suppliers. Drones should be GPS enabled when they are sold to customers to enable them avoid accidents with obstacles such as traffic, animals, and humans. Flight paths must be incorporated with additional constraints: examples include, height suited in the air apace they occupy; and the radius within which the drone can travel.

Automated pilots are a new and exciting area for Drones NZ and new models that are tailored to customer needs have recently started shipping The drones must maintain a log of delivery, time of start and finish and photographic record at the delivery end as well as all drone operational data and commercial customers must maintain other operational and environmental data such as GPS coordinates, altitude, directional data and speed data.

Recently, Drones NZ have publicized a means of providing customer feedback. Customers are prompted to provide feedback after every interaction with the business, as well through regularly sent emails and a link on their website. When customers provide feedback, they can attach their drone log of data to assist Drones NZ with their feedback. This has highlighted some areas that Drones NZ needs to improve on, such as service time, cost and autonomous drone performance.