1. **Data Driven Predictive Maintenance of Discrete Manufacturing System Components**
2. **Prognostics for gradual loss of conveyor belt tension in Discrete Manufacturing Settings**
3. **Power Consumption patterns for detecting gradual equipment wear and predictive maintenance in a factory automation system**

**Abstract: This paper presents a method that uses data-driven approach for prognosis of an incipient gradual behavioral deterioration of equipment used for transportation in discrete manufacturing systems, typically conveyor belts are used for transportation of material, pallets, or equipment between processing workstations of discrete manufacturing systems. This method relies on the power consumption information of conveyor belt motor driver which is collected under different workload and belt tension. The developed prognostic model is an artificial neural network (ANN) which learns conveyor belt driver engine’s power consumption pattern for a range of belt tension and workload (number of pallets residing on conveyor zones at a time) on conveyor belt. During run time, ANN model takes real time power consumption of conveyor belt driver engine and load data from testbench and predict a belt tension class. Consecutive mismatch between predicted belt tension class and optimal belt tension class is an indication of equipment failure, in current case it is an indication of gradual loss of belt tension, hence maintenance steps must be taken to avoid further catastrophic situation.**

# 1. Introduction

Modern discrete manufacturing systems composed of a lot industrial machines and equipment which are vulnerable to different faults. The consequences of these faults ranging from soft inconvenience to life-threating situations. Furthermore, gradual equipment failures in production systems remain un-noticed until the effects are serious enough which may cause on site jeopardizing situations. For production systems there is a certain cost associated with every occurrence of fault which includes production line shutdown, possible repair of collateral damage and parts, and labor for replacing the failed component or machinery. In addition to this, gradual deterioration of devices or equipment of a production system significantly affects the downtime of production machines or other heavy-duty equipment. Associated maintenance cost with the above-mentioned faults has significant impact on loss revenue. According to a study[1], the gradual wear of equipment is responsible for 3% to 8% decrease in oil production, causing up to $20 billion losses in the US economy.

Due to the associated risks and costs of failures, an early-stage equipment failure detection and prediction for prognosis maintenance is crucial to avert serious disruptions to production systems. To detect an incipient equipment wear, the data from plant sensors is utilized, for example data from vibration, temperature, pressure, and humidity sensors used in online maintenance[2]. In addition to the above-mentioned sensor data, energy consumption patterns associated with equipment or pieces of equipment is also promising to incipient a gradual equipment failure [3,4], an example of such fault is gradual loss of belt tension in conveyor belt operated transportation system in discrete manufacturing systems. In this work power consumption of conveyor belt motor driver repeatedly observed for a range of belt tension and workload. Obtained information is than used along with power consumption and workload information coming in real time from testbench, to detect a gradual loss of belt tension.

This paper is organized as follows: Section 2 briefly presents the theoretical background of this work and related research. Section 3 describes the testbed used. Section 4 gives details on the method used for detecting gradual loss of belt tension in conveyor belt in the discussed factory automation setting. Section 5 presents data analysis and results. Section 6 concludes and outlines future work.

# 2. Background

## Maintenance Strategies

The performance of a production system is significantly influenced by maintenance strategies adopted by site managers. A good and effective maintenance policy increases the equipment/machine life and extends its availability time, on the other hand an ineffective or poor maintenance strategy decreases both, equipment life and available time which leads to unexpected frequent sudden breakdowns. Two types of maintenance policies are being used in industry, known as reactive and proactive maintenance. Reactive maintenance policy includes Run-2-Failure strategy and proactive maintenance includes both preventive and predictive maintenances strategies [5].

Run-2-Failure (R2F) and preventive maintenance (PvM) are the two major maintenance strategies, used for production system. Fire-fighting maintenance, in literature also known as reactive, fault driven or Run-2-Failure maintenance strategy, is a maintenance strategy where maintenance activity starts when either equipment’s obvious functional failure, malfunction or equipment breakdown occurs. As it is a reactive maintenance strategy so corrective measurements are governed by random failure events and some time these failures leads to very large equipment or machine downtime, an extensive equipment repairing time as well as high repairing cost which decreases the production of a manufacturing system [5,6,7,8].

Preventive maintenance also, known as Time base maintenance which helps to slow down the equipment, component or machine deterioration by doing planned periodic plant inspection and repairs for example periodic lubrication and calibration etc. [6]. In preventive maintenance strategy, the part for maintenance is replaced on a specific date. This act makes sure a low possibility of sudden failure for the part involved. Compared to R2F, PvM provides more safety since a part failure is not mandatory prior to maintenance. But this is not cost-efficient enough, because some parts will be functional after the removal, so the replacement wasn’t necessary [7,8].

Predicted maintenance which is a type of condition-based maintenance, uses prognostic models to foretell the equipment, component, or machine condition. These prognostic models continuously monitor parameters of the under-test equipment or component and warns user as soon as parameters deviate from optimal values. These parameters come from sensors such as energy analyzer modules, temperature, vibration, corrosion, and humidity etc. These parameters used for training prognostic model which can foretell/predict the failure in test equipment before it occurs [6,7,8,9]. These models may be data driven, knowledge driven, or model driven, Figure1 shows taxonomy of predictive maintenance.

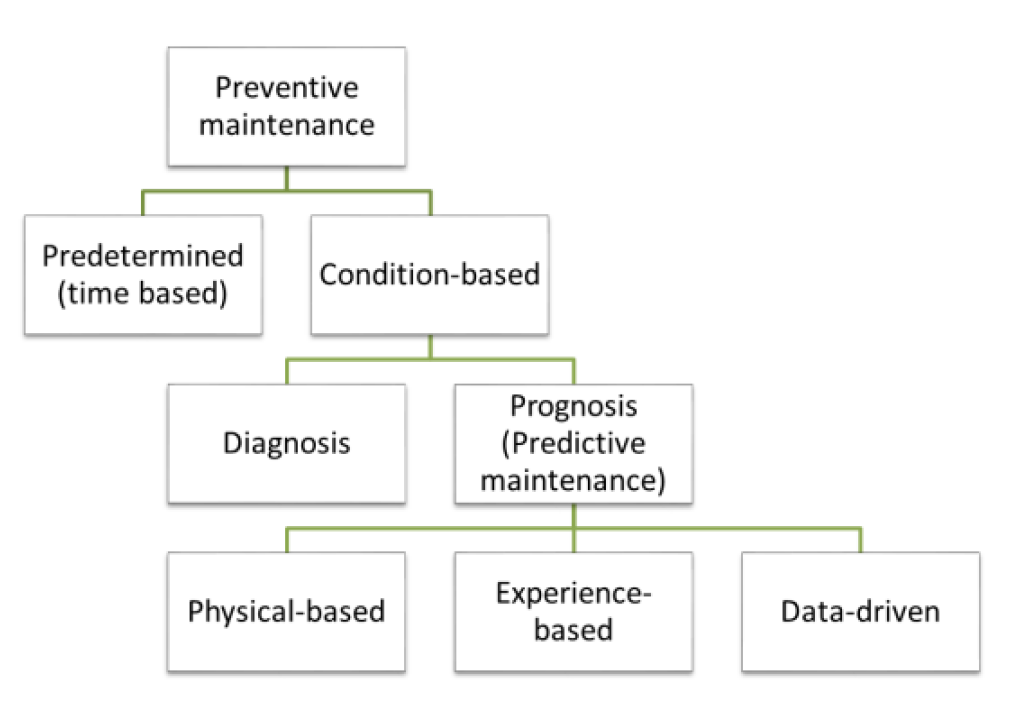


Figure 1: Taxonomy for Predictive maintenance [10]

State of the art prognostic models used for detecting and predicting faults in equipment are either data-driven or model driven. Model-driven fault prognosis model uses a mathematical model for system for analyzing the new incoming data from equipment. However, these models do not need any historical data for learning systems parameters. The disadvantage of this approach is to ensure accuracy of developed model as system complexity increases [12].

Data driven models use the historical observations of equipment data. For data driven fault prognosis system a mathematical model is not required [11].Data driven model learns the abnormal system behavior through machine learning techniques (ML) and statistical algorithms for example artificial neural network (ANN) or support vector machine (SVM) etc. Data driven models are applied for foretelling faults when the basic operating principle of a system is hard to model, or system is very complex. Data driven models are data hungry which is the biggest challenge associated with them as they require huge amount of good quality data for training as mentioned in [135], data-driven models require a good quality data up to two years. Due to limitations of model driven prognostic models, predictive maintenance uses data driven model.

State of the art Predictive maintenance techniques are either passive or active [14]. Passive maintenance techniques either use output signals from already existing on site sensors and verify performance themselves or uses the installed on-site test sensors to monitor the desire parameter (pressure, power consumption, vibration etc.) and use the installed sensor’s output signals to judge the performance by comparing the results with the expected results [2]. On the other hand, active maintenance techniques allow user to inject test signals to the equipment in real-time to observe the equipment’s response to the injected input as well as its modifications.

Mostly, for predictive maintenance data driven prognostic models are being used to predict equipment anomaly or gradual deterioration of a component so for good quantification of machine/equipment faults we need to provide a huge amount of good quality data for the training of the prognostic model which may be a ML or DL regression or classifier model. The collected data is used for investigating thresholds for healthy and unhealthy equipment’s operating regions as well as for training the model, for example in [15] real time vibration information is collected until failure to create a vibration-based database of suitable amplitudes associated with the bearing defective frequency and its first 5 harmonics.

## Artificial Neural Network

State of the art machine learning (ML) and deep learning (DL) algorithms can be used for predicting anomalies in industrial equipment or a machinery part. Algorithms offered by ML, learn system behavior and patterns from training data. Trained model is then used to make prediction on new incoming sample data while deep learning (DL) which is a sub-set of ML algorithms that uses one or more hidden layers with several processing neurons known as nodes, see Figure 2 [16].

Figure 2 show a simple ANN with one input layer having 3 nodes representing the data coming from sensors or desire equipment parameters, 2 hidden layers with 4 processing nodes and one output layer with one node. ANN are good at function approximation and system parameter learning with the feed forward and backward propagation respectively. The ANN learning process is extensively discussed in [17,18,19].

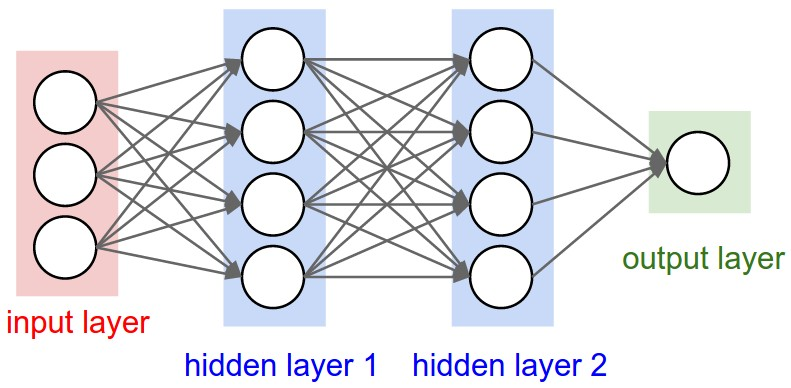


Figure 2: A simple ANN with 2 hidden layers

Different deep learning flavors like artificial neural network (ANN), Convolutional Neural Networks (CNN) Long-short term memory (LSTM) and Recurrent neural networks (RNN), are widely used in predictive maintenance due to their inherit ability to capture, learn and retain nonlinear failure patterns [21]. In [17,20], authors extensively review the DL algorithms, architectures as well as methodologies (supervised, unsupervised or hybrid) which are being used for predictive maintenance and presents a case study of engine failure prediction. According to [22] ANNs differ from traditional statistical techniques in their ability to successfully learn nonlinear features of a time series, and ANNs have been widely used in forecasting equipment health and failure.

In addition to other fields DL is also making its way in predictive maintenance day by day. Beside their positive aspects, deep learning models has a serious negative aspect which is related to data computational parameters as DL models need tons of data for training to produce quality results.

# 3. Testbench

FASTory line, see Figure 3, is used as a testbench in this research work. In past FASTory line was used in factory to assemble cell phone parts like frames, keypads, and screens. After retro fitting, FASTory line simulates its original cell phone assembling operations by drawing the main parts (frame, keypad, screen) of cell phone on a pallet in different shapes and colors. Figure 4 shows the layout of FASTory line.

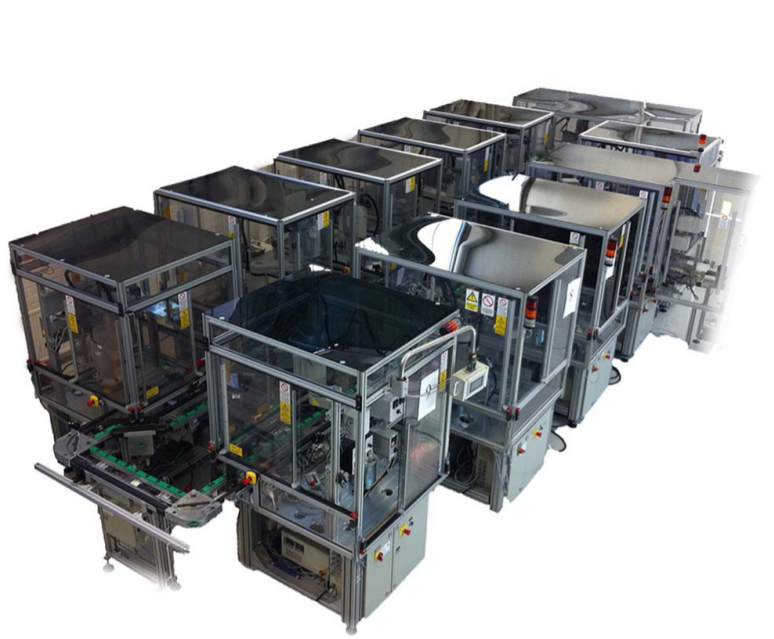


Figure 3: FASTory Line

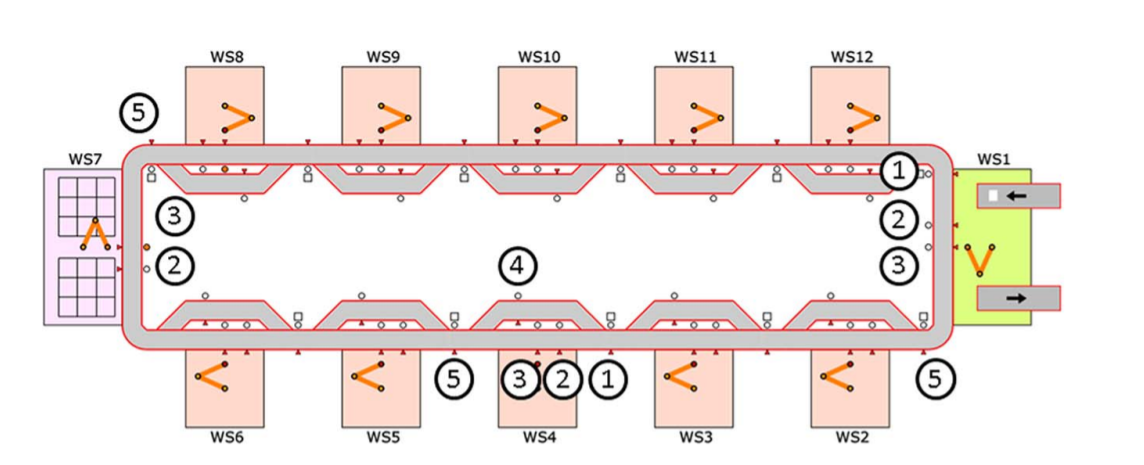


Figure 4: Testbench layout

The testbed comprises ten identical workstations, one buffer station and one paper loading and unloading station. W7 is the pallet buffer station, which is used for loading and unloading empty pallets, W1 loads a paper onto pallet for drawing and unloads the paper which contains the complete drawing of selected cell phone model. The remaining ten processing workstations are labeled W2–W6 and W8–W12. Each of this production workstation consists of one main conveyor, one bypass conveyor and one SONY SCARA robot, for workstations 2,6 and 9-12. Other cells have robots from OMRON, ABB and YASKAWA.

Each production workstation contains two conveyors: a main conveyor which transfers a pallet to the robot and a bypass conveyor moves the pallet to the next station once the workstation is busy. The FASTory line follows the closed loop topology which provides an uninterrupted path for pallets, thereby increasing the productivity/space ratio. Both conveyors split into different zones which are marked in Figure 4 and referred as Z# in this paper. The ins and outs of the workstations are located at Z1 and Z5 respectively. Main conveyor has four zones (Z1, Z2, Z3, Z5), for each zone there is a stopper and presence sensor for stopping and checking the presence of a pallet, Z3 is the production zone of each workstation. The Z1 of each workstation has a RFID tag reader at zone one which is used to read pallet ID also Z1 of next workstation and Z5 of current workstation are same. The bypass conveyor has one zone and one stopper and can process only one pallet.

The FASTory line is equipped with S1000 as well as an E10 energy analyzer module. S1000 is a smart, web service enabled controller which is being used for invoking operations and managing the shop floor equipment and devices. Besides providing the functionalities like a genetic controller, S1000 is capable to expose equipment data and methods from line as RESTful services [23]. Among such service the event subscription mechanism is developed. Such mechanism enables event-driven behavior in the system. Exposed event notifications (Table 1) include information about energy consumption (via S1000 energy meters), CAMX state events (e.g. pallet input to a conveyor piece etc.).

Table 1: Received Event Notification from Testbench

|  |  |  |
| --- | --- | --- |
| Sr# | Event Notification | Description |
| 1 | EnergyMeter | Robot/conveyor/controller energy consumption, of each working cell published at a time interval of one second. |
| 2 | DrawStart/DrawEnd | cell ID, recipe number, pen color  time stamp |
| 3 | EquipmentState | Cell ID, State of conveyor zones, pallet ID, time stamp |

# 4. Prognosis of gradual loss of belt tension in Conveyor belt operated transportation system

Belt conveyors are the most efficient equipment in industries because belt conveyors speed up transportation of materials and production times for example conveyor belts are used to transport sand, coal, and minerals etc. either powder or blocks over long distances in mining, metallurgy, paper, steel industries over long distances, on the other hand in discrete production system conveyor belts are used to transport equipment, pallets, and other tools between workstations. For proper and efficient material transportation, conveyor belts need certain traction force and belt tension to overcome the conveyance path friction. The traction force is provided by conveyor belt motor driver engine. For long distance industrial conveyor belts, DIN and CEMA standards are used for calculating required traction force, belt tension and other parameters to achieve optimal conveyor belt-based material transportation system. DIN and CEMA [24,25]. Once parameters are calculated, conveyor belt system is installed as well as nominal belt tension is adjusted for an efficient material transportation.

After installation and setup, conveyor belt system works efficiently until it has proper belt tension but with passage of time nominal belt tension of belt conveyor system starts losing. Loss in belt tension is a gradual process and remains un-noticeable until some serious faults occur in the transportation system or significant belt wear observed. Both too high and too low belt tension are harmful for conveyor belts. Too low belt tension leads to belt slippage on head pully which is one of the most common conveyor belt problems and it can lead to a whole cascade of additional problems for example spillage of materials, blockage of system, wear-and-tear and failure of the belt, damage or breakage to motors, motion failure and in some cases, even injury of employees. On contrast too high belt tension leads to an excessive stress on motor shaft, bearings which can damage driver motor as well as leads to uneven belt wears.

Traditionally, operators do weekly, bi-weekly, or monthly inspections of conveyor belts to keep everything health and working, i.e., follow scheduled preventive maintenance strategy, but to do so, they need to stop whole production plant or a sector of production plant which decreases plant production efficiency. This preventive maintenance strategy can be replaced with predictive maintenance strategy by carefully selecting and monitoring the parameters which describe behavior of conveyor belt and able to show parameter variation as soon as belt tension starts deviating from nominal value. These parameters could be data coming from vibration sensors, driver motor temperature, power consumed by driver motor etc. For this research work power consumption of conveyor belt motor driver is the interested parameter and regularly monitored under different belt tensions and workload. Obtained information from the analysis of power consumption pattern of motor driver under different cases is than used in along with power consumption and workload information coming in real time from testbench, to detect a gradual loss of belt tension.

## Monitoring relevant test bed generated data

For this research work, relevant data generated from testbench is related to power consumed by the conveyor belt motor driver. As mentioned in section 3, all workstations of FASTory line are equipped with E10 energy analyzer modules which is an expansion module to S1000 controllers and provides 3-phase electrical power consumption monitoring, see Figure 5. The connections to E10 energy analyzer module are as follow, Phase A is assigned to the robot, phase B is allocated to the cabinet, I/Os and the controller, while phase C is assigned to the conveyor system (including main and bypass). Power is measured by sampling current and voltage, the current sampled by a current transformer (CT) connected to +Ia-, +Ib- and +Ic- terminals and the voltage is measured by direct connection of the 3 phases and neutral to the Vn, Va, Vb and Vc terminals of the E10 expansion module. For this research work the phase C energy values are of interest for us.

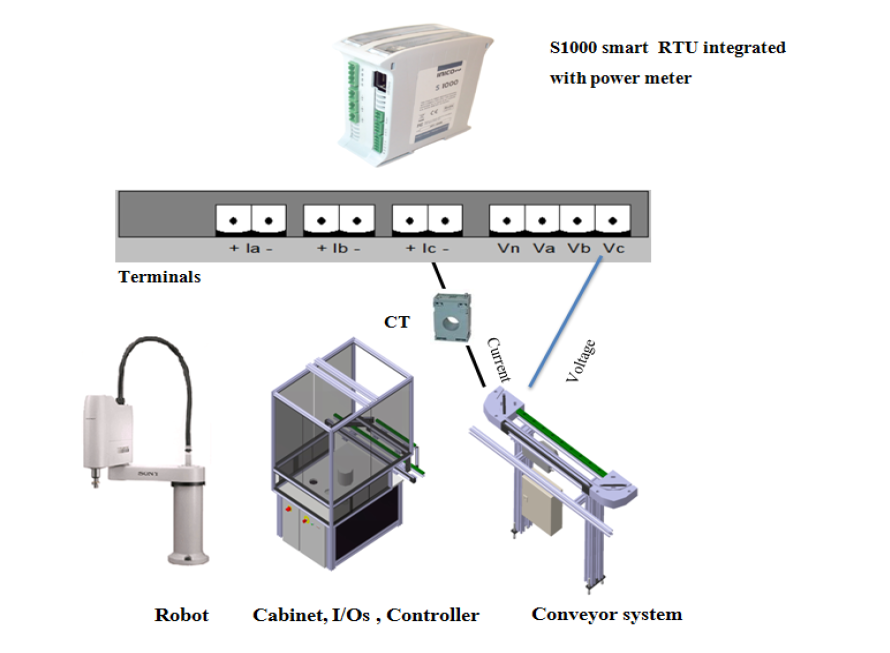


Figure 5: Monitoring Power Consumption in Testbench

## Data collection, preparation, and feature extraction

During this work data is collected for two separate cases “static case and dynamic case”. While collecting workload on conveyor and belt tension both are varied according to table 2 and table 3 respectively. The data collected in static case helps to investigate lower threshold (minimum belt tension which induce motion in the belt under no load condition) and upper threshold value of belt tension. Furthermore, it also provides information about, how active conveyor belt zones affects belt slippage and power consumption of belt motor driver. In addition to this, data from static case is used for training the ANN model. On the other hand, the data collected during dynamic case is used to investigate, how belt tension affects the movement of pallet between conveyor zones as well as transportation of material/tool/equipment between workstations. For each belt tension, this data helps to estimates the conveyor belt speed based on the time taken by pallet to move between zones of conveyor belt.

Power consumed by driver motor has a direct relation with tension in conveyor belt and workload i.e., the number of pallets occupying the conveyor at a time. As mentioned in section 3 the conveyor paths of FASTory line are divided into zones, for same belt tension the presence of a pallet on different zones has different effect on power consumption of the driver motor. Keeping the zone effect into consideration the power consumption data is collected for all zone according to zone combinations which are shown in Table 2. Belt tension is varied from 0% to 95% by changing the head pully position, according to values shown in Table 3. In short for each belt tension the experiment repeated for 16 times to get enough data to investigate relationship between conveyor belt tension, load on conveyor, and power consumption of conveyor belt’s motor driver.

To collect the data according to Table 2 and Table 3, main conveyor belt is running continuously, irrespective of weather pallets are residing on conveyor are stopped via stoppers or not. When stoppers are in use, there is an increase in friction between the conveyor belt and the pallet, which results in an increase of power consumption in the conveyor belt motor driver.

Table 2: Pallet position on Main Convoyer Zones with respect to Zone Combinations

|  |  |  |
| --- | --- | --- |
| Combination Number | Combination (Z1, Z2, Z3, Z5) | Description/Active Zone(s) |
| 0 | 0000 | No Load |
| 1 | 1000 | 1 Pallet at Z1 |
| 2 | 0100 | 1 Pallet at Z2 |
| 3 | 1100 | 2 pallets; One pallet at each zone (Z1, Z2) |
| 4 | 0010 | 1 Pallet at Z3 |
| 5 | 1010 | 2 pallets; One pallet at each zone (Z1, Z3) |
| 6 | 0110 | 2 pallets; One pallet at each zone (Z2, Z3) |
| 7 | 1110 | 3 pallets; One pallet at each zone (Z1, Z2, Z3) |
| 8 | 0001 | 1 Pallet at Z5 |
| 9 | 1001 | 2 pallets; One pallet at each zone (Z1, Z5) |
| 10 | 0101 | 2 pallets; One pallet at each zone (Z2, Z5) |
| 11 | 1101 | 3 pallets; One pallet at each zone (Z1, Z2, Z5) |
| 12 | 0011 | 2 pallets; One pallet at each zone (Z3, Z5) |
| 13 | 1011 | 3 pallets; One pallet at each zone (Z1, Z3, Z5) |
| 14 | 0111 | 3 pallets; One pallet at each zone (Z2, Z3, Z5) |
| 15 | 1111 | 4 pallets; One pallet at each zone (Z1, Z2, Z3, Z5) |

Table 3: Head Pully Position and % Belt Tension

|  |  |
| --- | --- |
| Head Pully Position (cm) from initial point | % Belt Tension |
| 0 | 0 |
| 0.5 | 15 |
| 0.85 | 30 |
| 1 | 40 |
| 1.2 | 45 |
| 1.3 | 50 |
| 1.6 | 60 |
| 1.8 | 70 |
| 2 | 75 |
| 2.3 | 85 |
| 2.5 | 95 |

Figure 6 illustrates the main steps for development of the data driven prognostic model for predicting the belt tension class. The data collected from FASTory line during static case is stored in a database for processing, analysis, and feature extraction at a later stage. During the collection of data, conveyor belt tension and the load on conveyor belt both are varied according to Table 3 and Table 2 respectively for investigating the lower threshold belt tension value (smallest belt tension which can put belt in motion) for no load condition as well as to capture the tiny effect on the conveyor belt motor driver due to the residing pallet and its position on the conveyor belt. The next step is to prepare data for analysis and feature extraction. After that features are modified as per ANN requirements. The ANN is trained on 80% training data, 10% data is used for validation and remaining 10% is used for model testing. When model is ready it is deployed for predicating the belt tension using the real time data from FASTory Line.

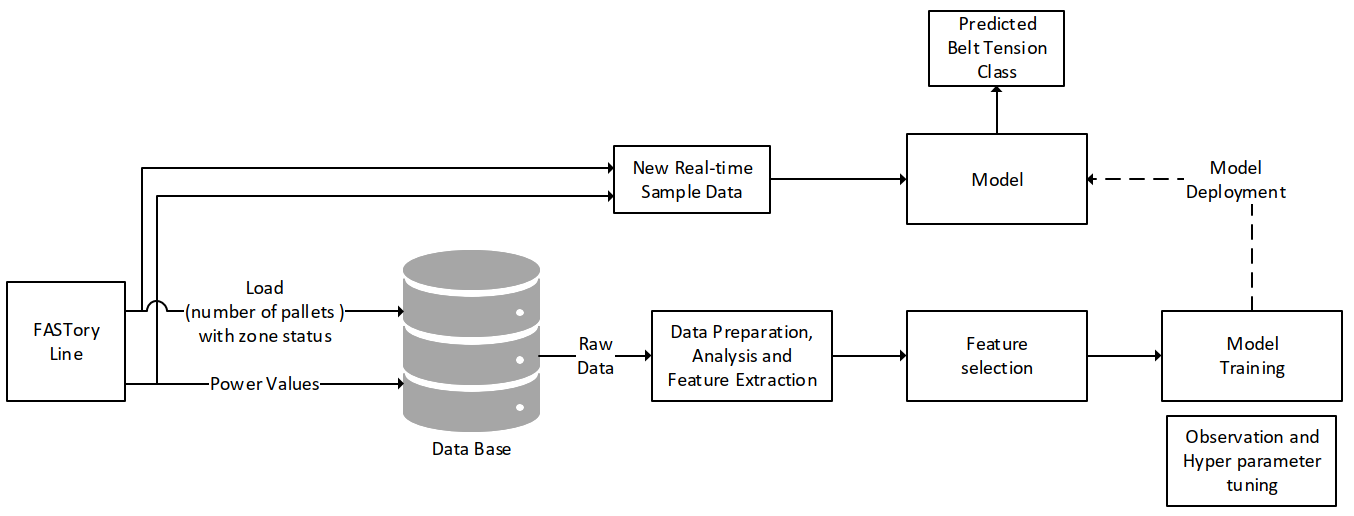


Figure 6: Main steps for development Data Driven Prognostic Model

# 5. Data Analysis and Results

In this section data collected for both static and dynamic cases will be analyzed thoroughly for each belt tension against all load combinations. As mentioned earlier, both too high and too low belt tension are harmful for conveyor belt, so analysis of static case data helps to investigate lower threshold (minimum belt tension which induce motion in the belt under no load condition) and upper threshold value of belt tension. Furthermore, it also provides information about, how active conveyor belt zones affects belt slippage and power consumption of belt motor driver. On the other hand, analysis of data collected under dynamic case is used to investigate, how belt tension effects pallet movement between conveyor zones and workstations of FASTory line.

## Analysis and Results for Belt Tensions 0% to 70%

During the experiment the belt tension was gradually increased from 0% to 95% according to Table 3 and load was varied on conveyor belt according to Table 2. For belt tension range 0% to 60%, it is concluded that these belt tension values are not useful for any operation because for these belt tensions, a sufficient frictional driving force was not generated between the driving wheel and the conveyor belt which led to belt slippage due to which load movement cannot be pulled. After a 10% increase in belt tension (70% belt tension), conveyor motor driver able to provide enough traction force to overcome path resistances and puts conveyor belt into motion without any load on conveyor belt. For 70% belt tension only combinations 0 and 1 are used to collect power consumption data because as soon as there is a pallet on zone one, belt speed significantly reduces due to lose of necessary required frictional driving force, also a jerky motion as well as belt slippage at head pully was observed. This jerky motion is harmful for conveyor belt health and causes the belt wear and tear which reduces belt life as well as increases production time. Figure 7 shows the box plots for belt tension ranging from 0% to 70%, the circles on boxes represents data mean. It can be seen from boxplots as soon as conveyor belt starts moving i.e., for load combination 0 at 70% belt tension the power consumption of the driver motor increases due to generation of frictional driving force between belt and head pully. On contrast, a decrease in motor driver power consumption is observed as soon as there is a pallet on the zone 1 of conveyor and reason is that the traction force generated with this belt tension is not enough to move the load on conveyor belt hence conveyor belt starts slipping from head pully.

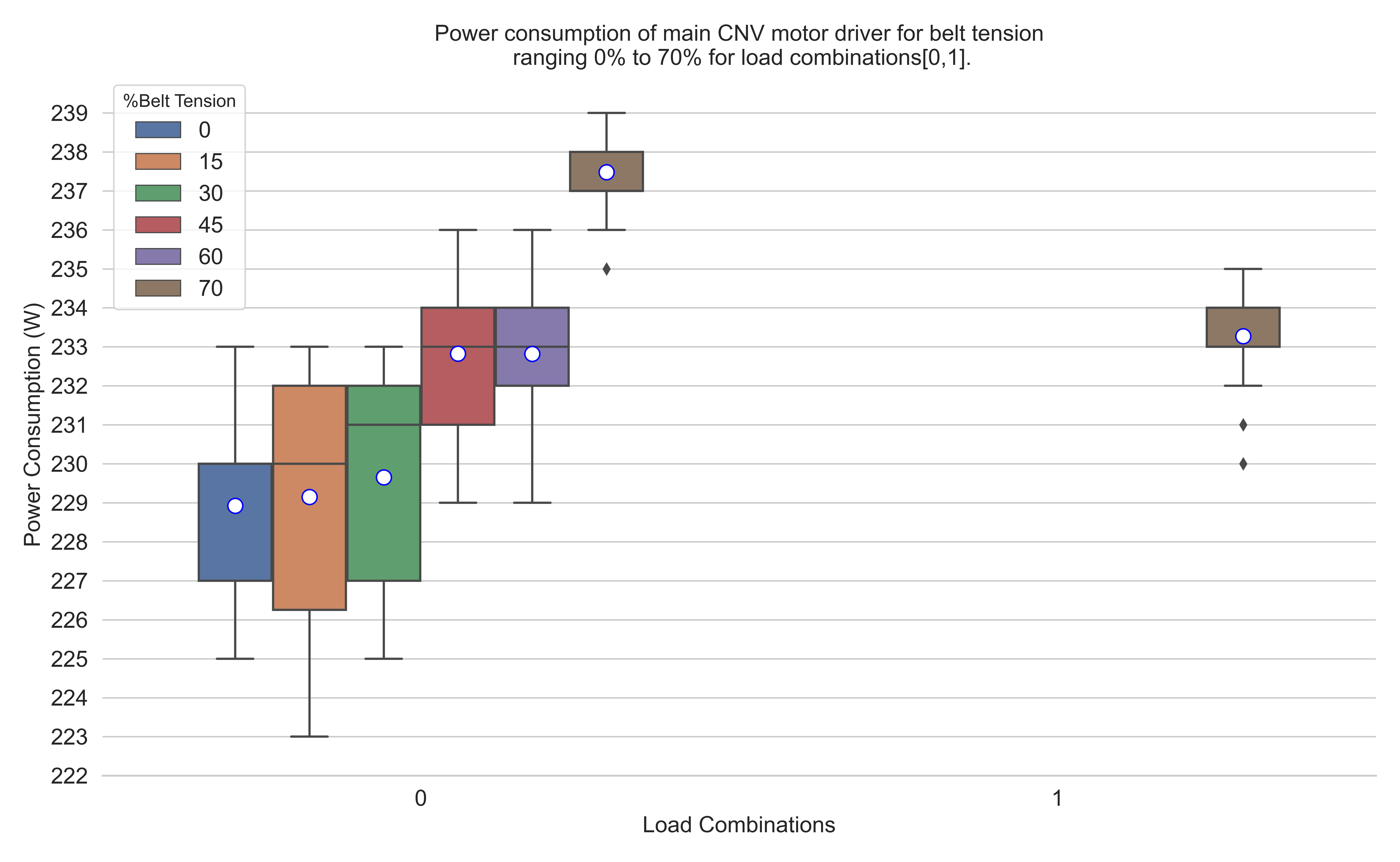


Figure 7: Effect of Belt Tension (0%-70%) and Load on Conveyor Motor Driver Power Consumption

Table 4 lists results for dynamic case data which shows how 70% belt tension affects the pallet movement between different zones of conveyor belt. As 70% belt tension does not provide necessary required frictional driving force to move pallets on conveyors which significantly increases material transportation time due to belt slippage and jerks. For this belt tension it took 120 sec for a pallet to move from Z1 to Z5. During experiment belt mis tracking was observed when pallet moves between zone 3 and zone 5 and pallet stuck at junction where bypass conveyor meets main conveyor and pallet never reach Z5.

From the analysis of results obtained from static and dynamic cases it is concluded that 70% belt tension is the lower threshold value i.e., minimum belt tension which puts the belt into motion without any load on conveyor belt.

Table 4: Dynamic Case results for 70% Belt Tension

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Belt Tension (%) | Active Zone | From | To | Distance(m) | Avg. Time(s) | Speed(m/s) |
| 70 | No | 1 | 5 | 1.61 | 120 | 0.013 |
| 70 | No | 1 | 2 | 0.61 | 80 | 0.008 |
| 70 | No | 1 | 3 | 0.835 | 86 | 0.01 |
| 70 | No | 3 | 5 | 0.773 | inf | 0 |

## Analysis and Results for Belt Tensions 75% to 85%

The results obtained for 75% belt tension are almost alike to 85% belt tension for all load combinations except for load combinations 6,7 and 14 (only Z2 and Z3 are dominated active zones) and 15 (all zones are active), for these combinations a reduction in belt traction force and an increase in belt slippage was observed. For 85% belt tension either no reduction in belt traction force or an increase in belt slippage was observed. For these belt tensions this experiment is conducted for all load configurations i.e., experiment is repeated for each load combination (Table 4). Figure 8 shows boxplot for 75% and 85% belt tensions which depicts effect of pallet position and belt tensions on conveyor belt motor driver’ power consumption.

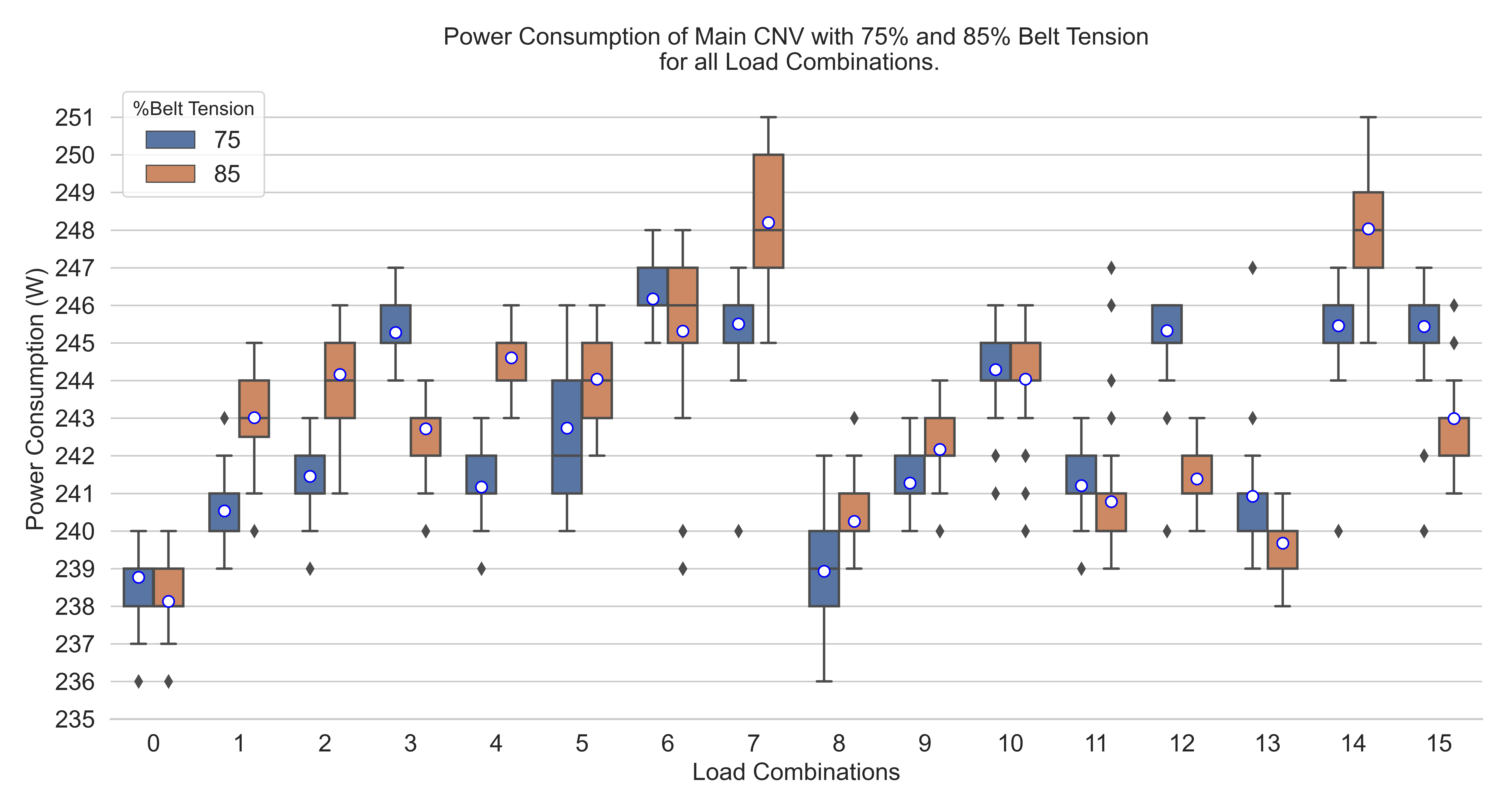


Figure 8: Effect of Belt Tension (75%-85%) and Load on Conveyor Motor Driver Power Consumption

Table 5 and Table 6 shows the dynamic case results for these belt tension with and without active zones. Refer to tables 5 and 6 it is observed that with 85% belt tension it took 5 sec for a pallet to move from zone 1 to zone 5 on the other hand it took 5.36 sec for a pallet to move from zone1 to zone 5 with 75% belt tension. One significant observation made for 75% belt tension, it took 4.24 sec for a pallet to move from zone 3 to zone 5 when two zones are active (Z1 and Z2) see Table 6, it is due to increase in friction along conveyance path, belt slippage and a reduction of required necessary frictional driving force between the driving wheel and the conveyor belt which due to which load movement is not as agile as in other combinations. Beside that there is no significant difference between the dynamic case results of these belt tension and no abnormal behavior of transportation, belt slippage and mis-tracking was observed for these belt tensions.

Table 5: Dynamic Case results for 75%-85% Belt Tension with no Active Zones

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Belt Tension (%) | Active Zone | From | To | Distance(m) | Avg. Time(s) | Speed(m/s) |
| 75 | No | 1 | 5 | 1.61 | 5.36 | 0.3 |
| 75 | No | 1 | 2 | 0.61 | 2.23 | 0.274 |
| 75 | No | 1 | 3 | 0.835 | 2.95 | 0.283 |
| 75 | No | 3 | 5 | 0.773 | 2.97 | 0.26 |
| 85 | No | 1 | 5 | 1.61 | 5 | 0.322 |
| 85 | No | 1 | 2 | 0.61 | 2.18 | 0.28 |
| 85 | No | 1 | 3 | 0.835 | 2.84 | 0.294 |
| 85 | No | 3 | 5 | 0.773 | 2.78 | 0.278 |

Table 6: Dynamic Case results for 75%-85% Belt Tension with Active Zones

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Belt Tension (%) | Active Zone | From | To | Distance(m) | Avg. Time(s) | Speed(m/s) |
| 75 | Z5 | 1 | 3 | 0.835 | 2.91 | 0.287 |
| 75 | Z5, Z3 | 1 | 2 | 0.61 | 2.29 | 0.266 |
| 75 | Z1, Z2 | 3 | 5 | 0.773 | 4.24 | 0.182 |
| 75 | Z1 | 2 | 3 | 0.223 | 1.2 | 0.186 |
| 85 | Z5 | 1 | 3 | 0.835 | 2.85 | 0.293 |
| 85 | Z5, Z3 | 1 | 2 | 0.61 | 2.07 | 0.295 |
| 85 | Z1, Z2 | 3 | 5 | 0.773 | 2.89 | 0.267 |
| 85 | Z1 | 2 | 3 | 0.223 | 1.02 | 0.219 |

## Analysis and Results for 95% Belt Tension

For this belt tension good and smoother belt motion is observed and there is no slip at head pully. Figure 9 illustrates, how conveyor motor driver power consumption is affected by belt tension as well as presence of load on different zones of conveyor at a time. For this belt tension a significant increase in power consumption observed for all load combinations. This is the maximum belt tension produced in conveyor belt by changing position of head pully. Too much tension will overstretch the belt and stress the motor bearings which can result into over amperage of conveyor belt driver motor and causes potential motor failure. So, this is an unhealthy operation condition which is harmful for both motor driver and conveyor belt and must be avoided. For this belt tension this experiment is conducted for all load configurations.

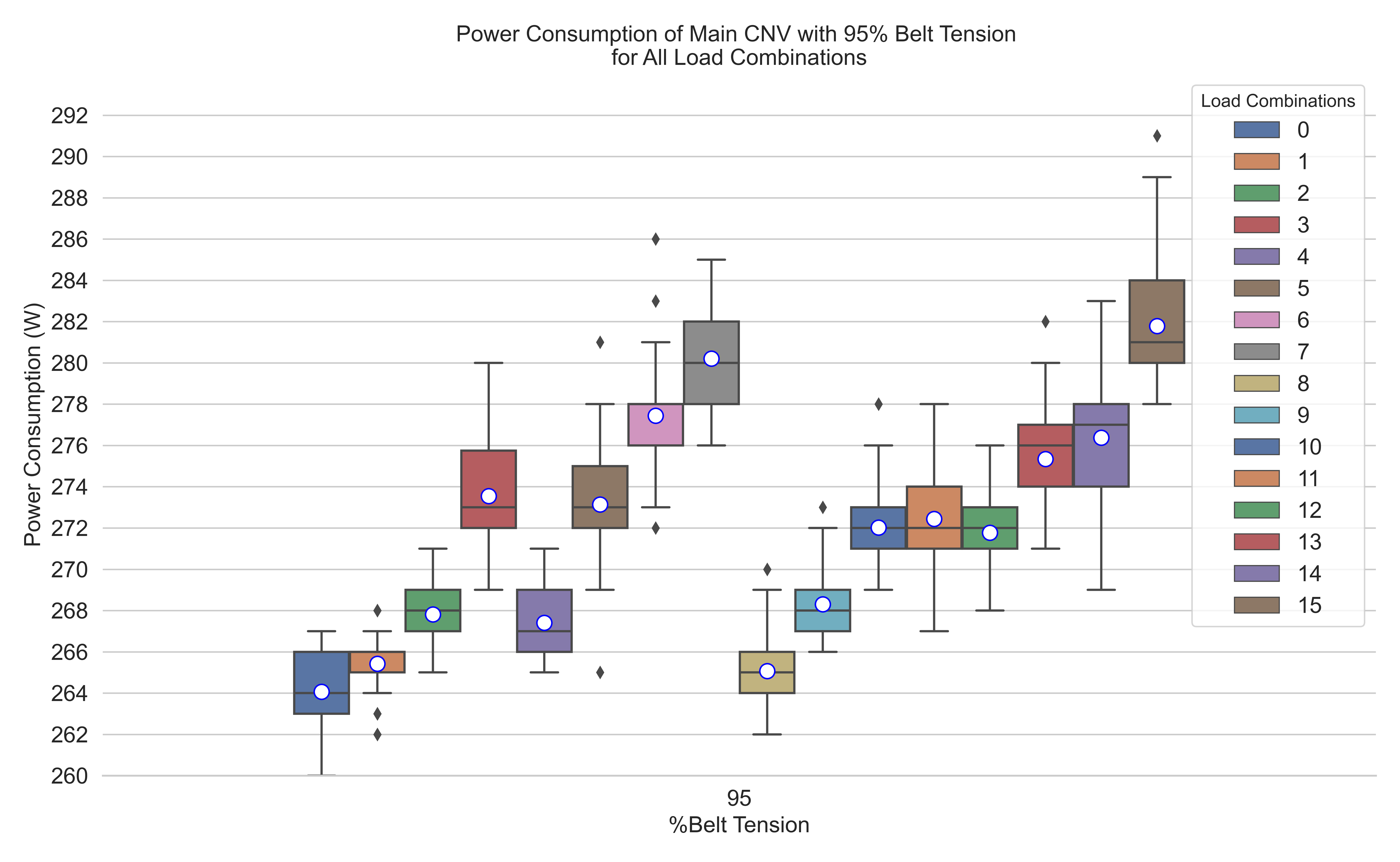


Figure 9: Effect of 95% Belt Tension and Load on Conveyor Motor Driver Power Consumption

Tables 7 and 8 shows they dynamic case results for 95% belt tension with and without active zones. Pallet movement is much smother then all the previous belt tensions and production time also reduced but belt stretch and stress on motor bearing are much higher.

Table 7: Dynamic Case results for 95% Belt Tension without Active Zones

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Belt Tension (%) | Active Zone | From | To | Distance(m) | Avg. Time(s) | Speed(m/s) |
| 95 | No | 1 | 5 | 1.61 | 4.6 | 0.35 |
| 95 | No | 1 | 2 | 0.61 | 1.98 | 0.308 |
| 95 | No | 1 | 3 | 0.835 | 2.86 | 0.292 |
| 95 | No | 3 | 5 | 0.773 | 2.77 | 0.279 |

Table 8: Dynamic Case results for 95% Belt Tension with Active Zones

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Belt Tension (%) | Active Zone | From | To | Distance(m) | Avg. Time(s) | Speed(m/s) |
| 95 | Z5 | 1 | 3 | 0.835 | 2.85 | 0.293 |
| 95 | Z5, Z3 | 1 | 2 | 0.61 | 1.99 | 0.307 |
| 95 | Z1, Z2 | 3 | 5 | 0.773 | 2.8 | 0.276 |
| 95 | Z1 | 2 | 3 | 0.223 | 1.02 | 0.219 |

As compared to 85% belt tension, minimum power consumption of 259.5 W was recorded at 95% belt tension for load combination 0 (no load) which is far greater than maximum power consumption (251 W) recorded at 85% belt tension for load combinations 3,7,14 and 15. Figure 10 shows comparison boxplots for belt tensions 75% to 95% belt tensions. For belt tensions 75% to 95%, conveyor belt motor driver power consumption varies between 235 W to 289 W and for belt tension 75% and 85% power consumption varies from 235 W to 251 W. As mentioned earlier 95% is the maximum belt tension that can be achieved in conveyor belt and any operation with this belt tension is harmful for both motor and belt itself and must be avoided.



Figure 10: Comparison of 75%,85% and 95% Belt Tensions

Similarly, Figure 11 shows comparison boxplots for belt tensions 0% to 85%. From analysis presented in previous section for belt tensions 0% to 70%, conveyor belt parameters remain same irrespective of the fact that for 70% belt tension there is motion in conveyor belt under no load condition but as soon as there is a pallet at zone 1 belt slip at head pully increase and power consumption drops to 232.2 W (data mean) hence leaving no separation boundary between 60% and 70% belt tension. So, all belt tension values which are less than or equal to 70% are treated as not useful belt tension value.

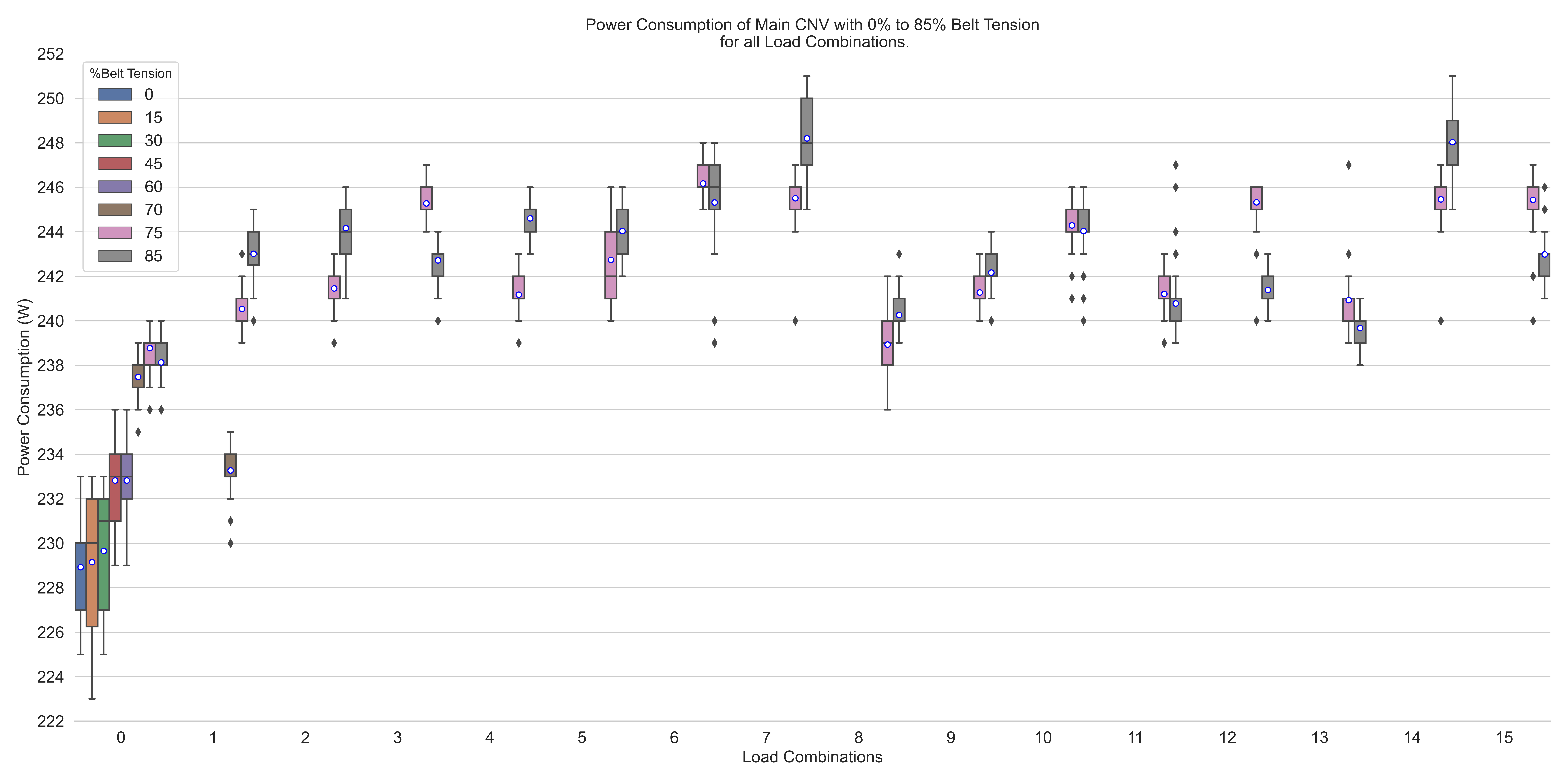


Figure 11: Comparison of 0%-85% Belt Tensions

Based on the data analysis and results described in previous sections, collected data can be classified in to three distinct belt tension classes, see Figure 12. Each box plot in Figure 12 represents power consumed by conveyor belt motor driver for all load combinations corresponding to the belt tension. As during analysis of static data, we observed that conveyor belt starts moving without any load for 70% belt tension and shows jerks as soon as there is a pallet on zone 1. On contrast for 95% belt tension on jerks and belt slippage was observed but belt stretch and stress on motor bearing are much higher than other belt tensions even belt tension squeals sound was audible and the belt tensions which are in between these two extremes shows moderate results hence the lower and upper threshold belt tension values are selected as follow,

In Figure 12 Boxplots, representing useful belt tensions are highlighted in green, lower threshold belt tension in yellow and over tense belt tension highlighted in red color respectively.

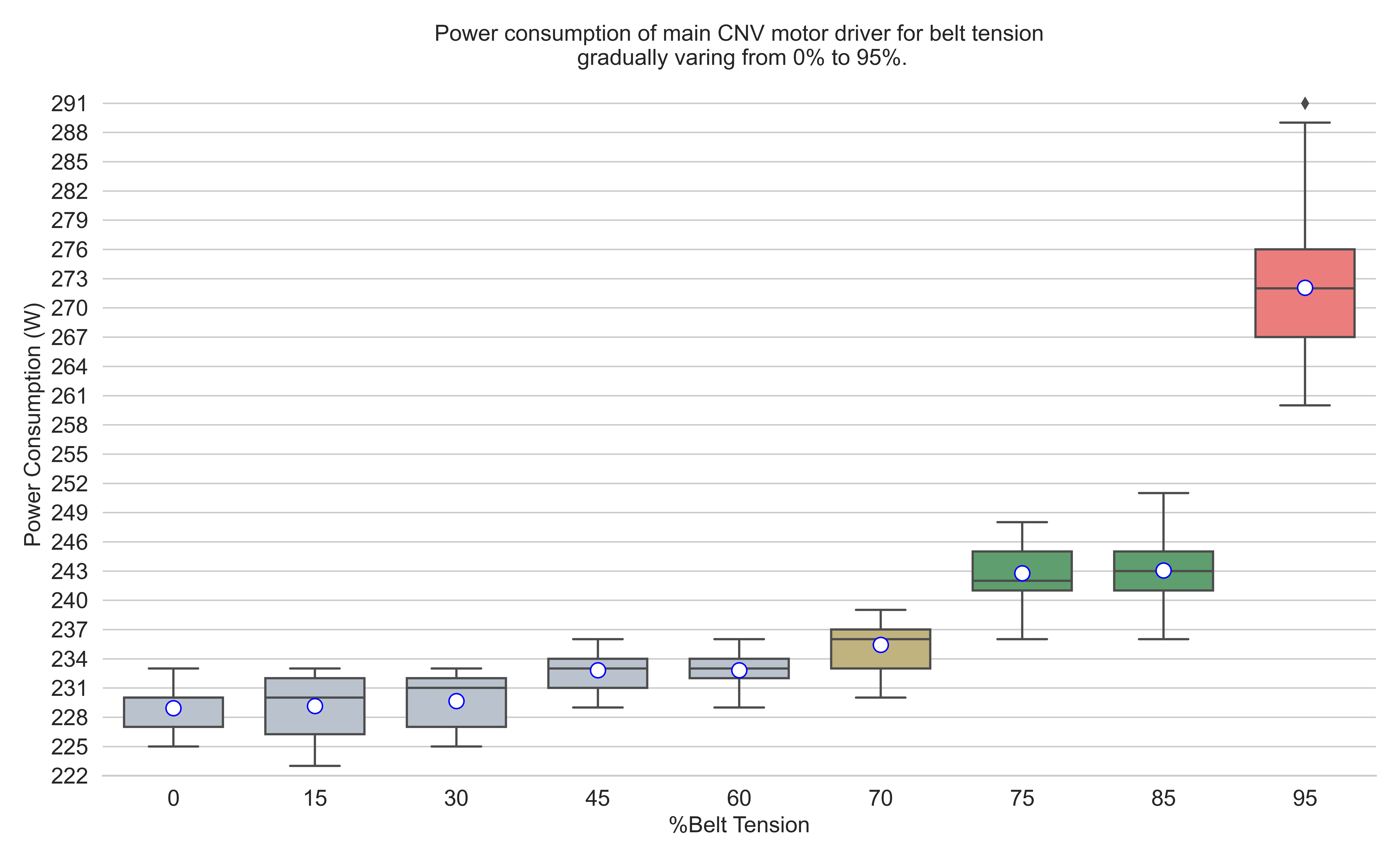


Figure 12: Cumulative Plot for all Load Combinations with Belt Tension Range 0%-95%

## Model Training and Prediction Results

The belt tension predictor model which is an artificial neural network is trained using the static case data with the aim to predict an early-stage behavioral deterioration of conveyor belts, i.e., gradual loss in belt tension so measurements steps will be taken beforehand to avoid further problems caused by belt slippage. This ANN is used for multiclass classification to predict a belt tension class Cm, where m is 1,2 or 3 which represents low, optimal and over tense belt tension class, see Table 9.

Table 9: Belt Tension Classes corelating to %Belt Tension Values

|  |  |  |
| --- | --- | --- |
| Class | Belt tension Values in % | Description |
| 1 | 0% to 70% | Not use full |
| 2 | 75% to 85% | Use full (nominal) |
| 3 | Belt Tension>90% | Not useful (over tense) |

Static case data includes more than 4500 data samples collected from FASTory line at a sampling rate of 1 second, out of these samples 80% are used for ANN training and 10% samples are used for validation, remaining 10% data samples are used for testing the model. The computed loss/error i.e. the average percentage of the number of unsuccessful predicted classes is 3.2%. This misclassification error observed for only those data samples that corresponds to no load situation i.e. load combination 0 for belt tensions 70%, 75% and 85% due data overlapping and low separation boundary. Another reason for this error is that the conveyor power consumption does not change instantly once conveyor workload is modified, but after a short time delay. This delay is responsible for the few outliers. Such occurrences may influence the value of the calculated error. Figure 13 illustrates data overlapping by plotting box plots for load combinations 0 and 1 with belt tension range 0% to 85%.

After testing, model is used for prediction on real-time data coming from FASTory line and prediction results are according to expectations. Like test data same misclassification observed for real-time and the reason of this misclassification is already explained, see Table 10 for misprediction results. Table 11 lists real-time prediction results for some data samples collected from 1500 real-time predicted data samples. During real-time prediction both belt tensions and load are varied by line operator according to Table 3 and Table 2 respectively.

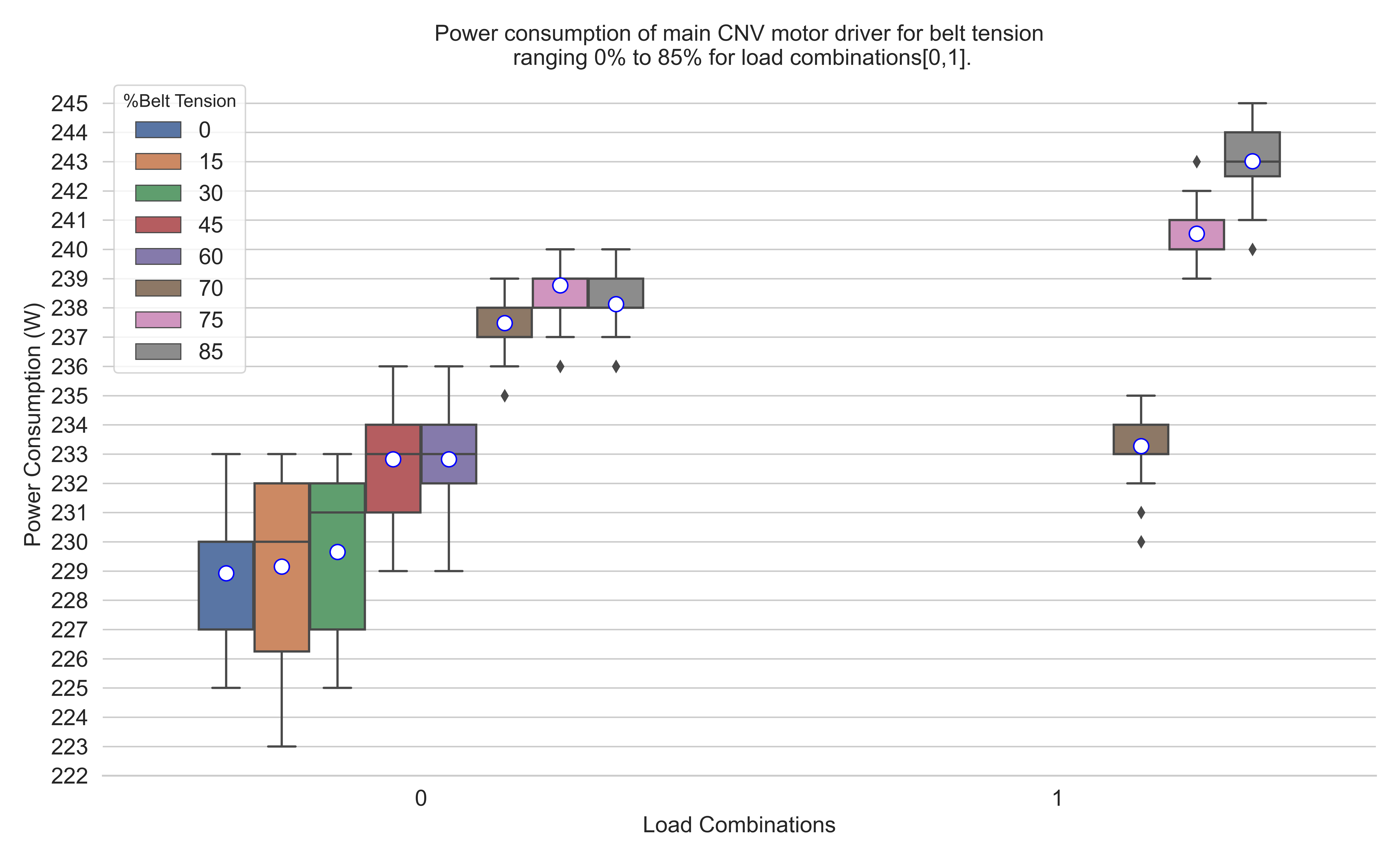


Figure 13: Misprediction Cause

The belt tension predictor model aimed to predict an early stage behavioral deterioration of conveyor belts. ANN model gets every second a new real-time data sample from FASTory line which contains power consumption values and load information. ANN model processes this new incoming data and predict a belt tension class. Through backend logic the newly predicted belt tension class is compared to last 10 predicted classes. Getting consecutive mismatch between new and last 10 predicted belt tension classes implies a gradual deterioration of belt tension from nominal belt tension range. Hence the power values observed no longer correlate as expected to the semantics defined statically, meaning that for each belt tension (Table 3) the belt driver engine consumes power within certain range.

Table 10: Mis predicted Classes

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **True Class** | **Power (W)** | **Load\_Combination** | **Active\_Zone** | **Pred\_Class** | **Time** |
| 2 | 232.6 | 0 | 0000 | 1 | 04/22/2021, 13:28:23 |
| 2 | 232.6 | 0 | 0000 | 1 | 04/22/2021, 13:28:24 |
| 2 | 232.554 | 0 | 0000 | 1 | 04/22/2021, 13:28:25 |
| 2 | 232.554 | 0 | 0000 | 1 | 04/22/2021, 13:28:26 |
| 2 | 232.52 | 0 | 0000 | 1 | 04/22/2021, 13:28:27 |
| 2 | 234.269 | 1 | 1000 | 1 | 04/22/2021, 13:29:27 |
| 2 | 234.269 | 1 | 1000 | 1 | 04/22/2021, 13:29:28 |
| 2 | 234.389 | 1 | 1000 | 1 | 04/22/2021, 13:29:29 |
| 2 | 234.389 | 1 | 1000 | 1 | 04/22/2021, 13:29:30 |
| 2 | 234.486 | 1 | 1000 | 1 | 04/22/2021, 13:29:31 |

Table 11: Results from 1500 real-time predicted data Samples

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **True Class** | **Power (W)** | **Load\_Combination** | **Active\_Zone** | **Pred\_Class** | **Time** |
| 1 | 229.855 | 0 | 0000 | 1 | 04/22/2021, 13:56:55 |
| 1 | 229.931 | 0 | 0000 | 1 | 04/22/2021, 13:56:56 |
| 1 | 230.124 | 0 | 0000 | 1 | 04/22/2021, 13:59:12 |
| 1 | 230.124 | 0 | 0000 | 1 | 04/22/2021, 13:59:13 |
| 2 | 235.945 | 2 | 0100 | 2 | 04/22/2021, 13:30:29 |
| 2 | 236.23 | 2 | 0100 | 2 | 04/22/2021, 13:30:33 |
| 2 | 237.16 | 4 | 0010 | 2 | 04/22/2021, 13:32:49 |
| 2 | 237.16 | 4 | 0010 | 2 | 04/22/2021, 13:32:50 |
| 2 | 237.481 | 8 | 0001 | 2 | 04/22/2021, 13:33:50 |
| 2 | 237.203 | 8 | 0001 | 2 | 04/22/2021, 13:33:51 |
| 2 | 233.321 | 9 | 1001 | 2 | 04/22/2021, 13:37:42 |
| 2 | 233.413 | 9 | 1001 | 2 | 04/22/2021, 13:37:43 |
| 2 | 234.881 | 10 | 0101 | 2 | 04/22/2021, 13:42:40 |
| 2 | 235.085 | 10 | 0101 | 2 | 04/22/2021, 13:42:41 |
| 2 | 236.684 | 12 | 0011 | 2 | 04/22/2021, 13:43:24 |
| 2 | 236.684 | 12 | 0011 | 2 | 04/22/2021, 13:43:25 |
| 2 | 237.733 | 13 | 1011 | 2 | 04/22/2021, 13:44:52 |
| 2 | 238.072 | 13 | 1011 | 2 | 04/22/2021, 13:44:55 |
| 2 | 244.243 | 14 | 0111 | 2 | 04/22/2021, 13:46:44 |
| 2 | 244.497 | 14 | 0111 | 2 | 04/22/2021, 13:46:45 |
| 2 | 244.134 | 14 | 0111 | 2 | 04/22/2021, 13:47:47 |
| 2 | 244.112 | 14 | 0111 | 2 | 04/22/2021, 13:47:48 |
| 2 | 243.037 | 11 | 1101 | 2 | 04/22/2021, 13:49:17 |
| 2 | 242.81 | 11 | 1101 | 2 | 04/22/2021, 13:49:18 |
| 2 | 243.188 | 13 | 1011 | 2 | 04/22/2021, 13:51:01 |
| 2 | 243.188 | 13 | 1011 | 2 | 04/22/2021, 13:51:02 |
| 2 | 247.281 | 15 | 1111 | 2 | 04/22/2021, 13:53:28 |
| 2 | 247.379 | 15 | 1111 | 2 | 04/22/2021, 13:53:29 |
| 3 | 252.693 | 0 | 0000 | 3 | 04/22/2021, 13:59:41 |
| 3 | 252.693 | 0 | 0000 | 3 | 04/22/2021, 13:59:42 |
| 3 | 255.959 | 1 | 1000 | 3 | 04/22/2021, 14:02:40 |
| 3 | 255.959 | 1 | 1000 | 3 | 04/22/2021, 14:02:41 |
| 3 | 256.048 | 2 | 0100 | 3 | 04/22/2021, 14:02:42 |
| 3 | 256.048 | 2 | 0100 | 3 | 04/22/2021, 14:02:43 |
| 3 | 257.72 | 2 | 0100 | 3 | 04/22/2021, 14:02:57 |
| 3 | 258.19 | 4 | 0010 | 3 | 04/22/2021, 14:04:54 |
| 3 | 258.19 | 4 | 0010 | 3 | 04/22/2021, 14:04:55 |
| 3 | 256.834 | 8 | 0001 | 3 | 04/22/2021, 14:06:28 |
| 3 | 256.501 | 8 | 0001 | 3 | 04/22/2021, 14:06:29 |
| 3 | 279.917 | 9 | 1001 | 3 | 04/22/2021, 14:08:02 |
| 3 | 280.485 | 9 | 1001 | 3 | 04/22/2021, 14:08:03 |
| 3 | 279.053 | 10 | 0101 | 3 | 04/22/2021, 14:08:46 |
| 3 | 279.053 | 10 | 0101 | 3 | 04/22/2021, 14:08:47 |
| 3 | 280.309 | 12 | 0011 | 3 | 04/22/2021, 14:10:21 |
| 3 | 280.309 | 12 | 0011 | 3 | 04/22/2021, 14:10:22 |
| 3 | 287.266 | 13 | 1011 | 3 | 04/22/2021, 14:11:54 |
| 3 | 287.151 | 13 | 1011 | 3 | 04/22/2021, 14:11:55 |
| 3 | 282.805 | 14 | 0111 | 3 | 04/22/2021, 14:13:02 |
| 3 | 282.805 | 14 | 0111 | 3 | 04/22/2021, 14:13:03 |
| 3 | 286.667 | 15 | 1111 | 3 | 04/22/2021, 14:14:59 |
| 3 | 286.667 | 15 | 1111 | 3 | 04/22/2021, 14:15:00 |
| 3 | 288.67 | 11 | 1101 | 3 | 04/22/2021, 14:15:01 |
| 3 | 288.67 | 11 | 1101 | 3 | 04/22/2021, 14:15:02 |
| 3 | 298.24 | 7 | 1110 | 3 | 04/22/2021, 14:18:44 |
| 3 | 298.24 | 7 | 1110 | 3 | 04/22/2021, 14:18:45 |

# 6. Conclusion and Future Work

This paper presents a method that uses power signature of a well-behaved system to describe the expected system behavior. In summary, power consumption values of a conveyor belt-based transportation system in a cell phone assembling line were monitored and classified for a real factory automation testbed. During training phase, the power signature of the system components and workload of the conveyor belts is associated with semantics concerning the conveyor belt tension and at validation phase, real time data coming from the line is input to the predictor model which predict the belt tension class. Consecutive mismatch between new and last 10 predicted belt tension classes implies a gradual deterioration of belt tension from nominal belt tension range which pinpoints to an incipient gradual deterioration of expected behavior of equipment. In the presented scenario, such deterioration would translate to a gradual loss of belt tension of conveyor and maintenance steps must be taken for equipment to avoid catastrophic hazards.

Future research will focus on bringing more parameters for analysis and increasing the number of dimensions of the available datasets by installing vibration and temperature sensors for conveyor belt motor driver.