IMPACT OF LEAN AUTOMATION ON PROCESS PERFORMANCE IN SUGAR INDUSTRIES IN KENYA: CASE OF MUMIAS SUGAR COMPANY

BY

EMMANUEL AUSTINE EBINGA OSORE

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Declaration

This thesis is my original work prepared with no other than the indicated sources and support and has not been submitted anywhere for award of a relevant degree or any other award.

....17/11/2020......

Emmanuel Austine Ebinga Osore

F80/50496/2016

Date

The undersigned certify that they have read and hereby recommend for acceptance of the thesis entitled: **Impact of lean automation on process performance in sugar industries in Kenya: Case of Mumias Sugar Company.**

.... 17/11/2020

Prof. Eng. Julius M. Ogola

Department of Mechanical and Manufacturing Engineering

University of Nairobi

Date

.... 17/11/2020

Prof. Madara M. Ogot

Department of Mechanical and Manufacturing Engineering

University of Nairobi

Date

.... 17/11/2020

Prof. George Nyori

Department of Mechanical and Production Engineering

University of Eldoret

Date

Dedication

To my wife Felister, my daughter Rachael and sons Philip and Michael for being a source of inspiration throughout this research.

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Abstract

Several challenges like high cost of production continue to affect the performance of sugar industries depicted by undesirable process efficiencies and productivity with average sugar productivity of 85%, which is below 92% recommended world average. This is attributed to lack of a holistic application of key components of lean thinking applied prior to adoption of advanced techniques like automation to reap maximally and more importantly enhance their process performance. More specifically, sugar industries in Kenya operate on conventional automation (LoA 4) among other factors for monitoring and controlling processes. Also, proper sensitization of lean automation and its impact on the performance of industrial competitiveness of sugar industry in Kenya is non-existence. This has resulted to uncompetitive and unsustainable process performance leading to collapse of Kenyan sugar companies. Lean automation is the technique of applying the optimum level of automation to a lean environment with a focus on robustness, reliability and minimization of complex tasks. With the objective of assessing the effects of lean automation through advanced LoA for full benefits, an experimental design in a case sugar industry was conducted to assess the status of real world circumstances for optimum level of automation. The indicators of lean manufacturing integrated with proper level of automation on sustained performance was assessed and compared, and the potential of lean automation simulated. Based on adaptive control, both LoA 5 and 6 recorded the lowest index of 0.21 compared to 2.1 for LoA 4 due to rapid changeover within a shortest time, thus LoA 5 and 6 ideal for real time monitoring. For quality in production, LoA 6 recorded the highest index of 84.96 compared to 84.03 and 81.29 recorded by LoA 5 and 4 respectively. Implying that, LoA 6 enables mornitoring and attainment of optimum performance of process parameter. Similarly, the continuous improvement index of 175.0, 430.0 and 430.0 for LoA 4, LoA 5 and LoA 6 respectively depicted a lower rate of production for LoA 4 at 100 T/h compared to LoA 5 and 6 at a rate of 360 T/h. For wastage reduction, LoA 6 recorded the least resource utilisation index of 2101.2 compared to 2103.6 and 3311.2 for LoA 5 and 4 respectively. This is as a result of minimum variations in the process parameters due to their real time monitoring and control with LoA 6. Finally, the overall process performance index for LoA 4, LoA 5 and LoA 6 was 65.69, 147.56 and 147.79 respectively. It is evident that lean automation which consists of LoA 5 (SCADA) and LoA 6 (DCS), provides the optimum AMT that the local sugar industry require to attain a sustainable and competitive process performance. Therefore, it should be considered for adoption and implementation within the sugar processing line as the appropriate AMT that will enable real time monitoring of process variables, minimization of resource wastages, quality production and continuous improvement in the sugar industry

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Abbreviations and acronyms

SCADA – Supervisory control and data acquisition

DCS- distributed control system

PLC – Programmable logic controls

LoA – Level of automation

PS – Weigh bridge stage

CL – Cane loading stage

FT – Feed table and Kicker stage

KNIV – Knives stage

MC – Main cane carrier stage

SHREDD – Shredding stage

HD KNV – Heavy duty Knives stage

EXTRACTN – Juice extraction stage

α – Significance level of data analysis

VFD – Variable Frequency drive

CSD – Constant speed drive

VSD – Variable speed drive

VIF - variance inflation factor

CI – Confidence interval

PID – Proportional, Integral, Derivative control

MT – Metric ton

COMESA – Common Market for Eastern and Southern Africa

FTA – Free Trade Agreements

VHP – Very high polarity

AMT- Advanced Manufacturing Technology

T/h – Tons per hour

Terminology and Definitions

%**pol** - The apparent sucrose content of any substance determined by a polarisation method and expressed as a percentage by mass or in degrees Z (°Z).

Absolute juice: a hypothetical juice, the mass of which is equal to the mass of cane minus the mass of fibre. It comprises all the dissolved solids in the cane plus the total water in cane.

Bagasse - The fibrous residue obtained after crushing cane in a mill

Brix is - the percentage by mass of soluble solids in a pure sucrose solution.

Extraction - is the ratio of sucrose (or pol) in mixed juice to sucrose (or pol) in cane expressed as percentage and is an indication of the theoretical efficiency of the extraction process.

Fibre is the water-insoluble matter of cane and bagasse from which the Brix-free water has been removed by drying

Glucose (also known as grape sugar) is a monosaccharide and a reducing sugar

High performance liquid chromatography - Generally referred to as HPLC this is a widely known technique to very accurately determine the quantity of a specified substance in a sample. HPLC is routinely used in the Southern African sugar industry to determine the amount of sucrose, fructose and glucose in molasses.

Imbibition is - the process in which water or juice is put on bagasse to mix with and dilute the juice present in the bagasse. The water so used is termed imbibition water.

Liming - The addition of lime to mixed juice for the purpose of clarification

Mean circumference: mean diameter x p.

Mill ratio - the ratio of feed to discharge work openings.

Preparation Index (PI) is the ratio of Brix in the ruptured cells to total Brix in cane expressed as a percentage. PI is an empirical method and uses the ratio of the Brix's obtained using two different cane preparation methods.

Set opening - the distance between the circumferences escribed by the mean diameters of the top roller and feed or discharge roller with the mill running empty.

Sugar cane is botanically a tall grass of the type Saccharin and agriculturally the crop produced from hybrids that are the descendants of a number of Saccharin species commonly referred to as sugar cane and is the raw material accepted at the cane sugar mill for processing.

CHAPTER 1 : INTRODUCTION

1.1. Background Information

The Kenya's manufacturing industry, in which the sugar industries belongs, has declined in its GDP contribution. The stagnation has been at an average of 10% for more than ten years, with Sugar industry contributing 41% decrease in manufactured products (Mwangi, 2018). The Kenya vision 2030 stipulates that the industry should account for a GDP of 20%. Attaining this goal need underlying constraints which hinder rapid growth be addressed. The constraints include technological inadequacies, high input costs, and decrease in investment portfolio and increase in credit and competition costs from imports (Otieno, 2015). In Kenya, there are 11 operational sugar factories namely: Mumias Sugar Factory, Chemelil Sugar Factory, Nzoia Sugar Factory, Kibos Sugar and Allied Factories, Muhoroni Sugar Factory, Transmara Sugar Factory; South Nyanza Sugar Factory, Sukari Industries Limited, Kwale International Sugar Company, West Kenya Sugar Factory and Butali Sugar Factory. (Kenya National Assembly: March, 2015).

As reviewed by Ondiek and Kisome (2013), in spite of the availability of these companies, as highlighted by KESREF (2010), sustainability and self-sufficiency in sugar production continues to drop as consumption demands continues to increase. Several challenges continues to affect the performance of sugar industries depicted by undesirable process efficiencies and productivity with average sugar productivity of 85%, which is below 92% recommended world average. In Kenya, the sugar production cost is approximately Ksh 46,000 per metric ton, and this is almost twice that of countries like Swaziland in Southern Africa register which is Ksh 24,000, KESREF (2010) confirms.

According to Ondiek and Kisome, (2013), it will be beneficial if sugar industries in Kenya can give consideration to the holistic application of key components of lean thinking, so that they can reap maximally and more importantly enhance their process performance among them lead time. These lean techniques among them employee involvement, visual display and control, 5S, and standardization are applied prior to adoption of advanced techniques like production smoothing and value stream mapping. This is because the advanced methods can only be implemented when there is good quality, stable machine condition and good layout.

Current studies in the sugar industries show that, instead of a holistic approach, lean thinking is not embraced or employed selectively with no regard to its knowledge and principles. The optimum outcomes of a production system therefore, requires a proper determination and integration of all the related and associated advanced technology. Thus, this study will investigate the impact of integrating levels of automation with a holistic implementation of lean manufacturing techniques to satisfy customer needs. With the help of process indicators namely lead and cycle times, product quality and frequency of injuries, the effectiveness of this integration can be evaluated (Ondiek and Kisome, 2013).

1.1.1. Automation

In advanced manufacturing technology, four fields are pertinent namely: additive manufacturing, automation, fabrication and precision engineering (Mitchell, 2012). Automation is the application of software and control circuitry to autonomously monitor and manipulate mechanical processes in an industry (Jonsson, 2013). According to Kalpakjian and Schmid (2008), automation may be grouped into 6 categories namely:

a. Numerical control, which involves the automation of machine tools through programmed commands. Most numerical control is undertaken via computers, applying computer numerical control (CNC), which manufacture specific products according to input programs.
b. Adaptive control, which creates a control method with adaptable parameters for changing their response according to the desired model.
c. Material handling, which involves the transfer, monitoring, regulation and storage of both finished and raw products along the process line.
d. Robotics, which refers to automated machines that may replace the role of people in manufacturing processes.
e. Assembly, which involves the mechanical act of combining components in manufacturing systems.
f. Flexible fixturing, which enables machines to hold a variety of fixtures.

Granlund (2012) alluded that, automation as an advanced manufacturing technique, is mainly divided into two categories namely: mechanization and computerization. Mechanization is related to the physical flow of goods while computerization is the flow of information. According to Frohm (2008), automation can lead to many benefits depending on the type of industry, among them: improved working environment, increased throughput, flexible material handling, less workforce, improved productivity, reduced costs, and improved quality. However, in lean environments, if the same automation is not well planned, it may cause challenges ranging from maintenance, difficulties in visualization, time consumption, and difficult machine-human interface.

Automation can be regarded as either fully automated or fully manual, and it is aimed at acquisition of value addition, better process throughputs and increased productivity (Winroth et al., 2006; Orr, 1997). Similarly, the competitive approach of reducing the unit cost of a product agitated the need for a faster production pace, and this is through automation of crucial tasks (Ribeiro and Barata, 2011). In addition, there are extreme ordinary situations where human intervention is impractical and thus calls for the implementation of automation. (Harris and Harris, 2008). Examples are hazardous products, sensitive nanotechnology components, accuracy, high tolerance components and strenuous activities. Therefore, automation provides an excellent ergonomics (Kochan, 1998).

For optimum technological solutions, an integration of automatic and manual functions of a manufacturing plant to have semi-automatic processes will result into efficient monitoring and control of both physical and statistical quantities that affect the processes. This integration will result to the so called level of automation that ranges from purely manual to fully automated process operations. Choosing an optimum level of automation will have a positive outcome on the manufacturing process, contrary to if automation is under or over applied (Säfsten et al., 2007).

Therefore, this study focused on how automation adoption impacts on the industrial process performance. The principle of automation adoption was represented by the level of automation. The automation objective considered was material handling and adaptive control, since they are the most predominant in the sugar process line.

1.1.1.1 Levels of automation

Level of automation is the extent to which automation is employed within the production line. There are different models for work functions the describe level of automation. According to Harris and Harris (2008), there exist five levels of automation in manufacturing. Level 1 consist of pure manual tasks by an operator. In level 2 the loading onto the machine is done manually by an operator, followed by an automatic machine cycling or operation, then manual unloading and transfer of the machined part to the next manufacturing stage. In level 3 the loading is done manually by the operator, next the machine cycles automatically, same to unloading of the part from the machine. Finally, the part is transferred manually by the operator to the next stage. In level 4, the part is loaded automatically, followed by automatic machine cycling, automatic unloading and finally manual transfer to the subsequent production stage. Level 5 is fully automatic, that is loading and cycling, unloading and transfer of parts are all automated.

Another model for work functions was developed by Sheridan and where LoA was classified as LoA 1 (with work functions totally manual) to LoA 10 (with work functions totally automatic) (Lindström et al., 2006). Groover (2000) also proposed three automation levels and three different layout. The material handling equipment represents technologies at level 2, although some of the handling equipment is sophisticated. In all these levels, the working environment should be properly selected. However, a different model was suggested by Garcia (2015) with six levels of automation. This is referred to as the six-sigma levels of automation.

In all these models, it was observed that automation enhances efficiency, quality and reduces cost of production. It permits much greater manufacturing flexibility, that is, products which have larger volumes or ergonomically awkward to manipulate can be produced in an easy way.

Since automation focuses on problems related to human engineering, different LoA can give different results that needs to be studied. In this regard, the study adopted Garcias's model and looked at only three LoA namely LoA 4, 5 and 6. LoA 5 and 6 represents lean automation while LoA 4 is the conventional LoA as the control experiment (Garcia, 2015).

1.1.2. Lean manufacturing

Lean which is implemented majorly by Just in time (JIT) technique focuses on waste elimination. This implies adoption of minimal manpower, space, investment in equipment and tool, lead times, inventory and manufacturing defects among others. This reciprocates well with Just in time implementation which aims at improving quantity, inventory, and lead times cycles, investment cost, staff welfare and workforce productivity (Fullerton and McWatters, 2001). In Japanese waste is called *muda*, which is any activity that utilizes inputs but doesn't create any outcomes. The efficiency of a lean organization is realized when inputs are spent on productive activities. The only challenge though in our sugar industry is monitoring and control of these activities (Orr, 1997). In this study, the following three lean manufacturing indicators were adopted to facilitate JIT in achieving better process performance: rapid changeability, waste reduction and system improvement.

Lean depends on personal responsibility and customer satisfaction to the level which customer specifies (Chen, 2010). Lean manufacturing is considered to be an enhancement of mass production, hence it is assumed not to be a new technique. Its objectives are to maximize profit by reducing costs and waste of material and improving quality, in such a way one can say these are essentially the underlying principles of mass production (Mehrabi, 2002). To enhance reduced inventory, just in time (JIT) a Japanese word for *kanban,* is the philosophy that can achieve smooth supply chain flow of parts. This will facilitate manufacture of what is needed without waste and subsequently reduced wastes. However, the Kenyan Sugar industries fail short of holistic implementation of lean manufacturing and this provides a gap that needs to be addressed.

1.1.3. Lean automation

The term lean automation refers to the technique of applying the optimum level of automation to a lean environment with a focus on robustness, reliability and minimization of complex tasks. One pillar of lean manufacturing is the *jidouka* meaning autonomation, it implies automation together with manpower. Autonomation focuses on adoption of unique tasks or equipment to detect any abnormal and undesirable defective state of the production process (Jackson et al., 2011).

According to Orr (1997), Hedelind and Jackson, 2008b, Hedelind et al., 2008a lean automation has been successful in the motor industry by Toyota motors in relation to robotics, Computerized Numerical control and assembly and proved that it can enhance the repair and maintenance of processes since they can incorporate maintenance programs like predictive, preventive and total productive maintenance. On the other hand, it has not been incorporated in the sugar industry, thus giving a research gap to determine the effectiveness of lean automation on optimum performance of sugar industries.

1.1.4. Process performance

According to Garcia (2015), any industrial activity can either lead to value addition or cost addition (waste).Value addition is only when there is physical conversion of a product to the customers' intention or provision of services that satisfies the worth of a customer's money in terms of design and engineering. In most sugar industries, 90% of the process lead time does not add value and therefore, needs elimination. As attributed to Shaman and Sanjiv (2013) and Wong et al. (2009) through their research, continuous improvement and waste reduction tools are vital elements of lean manufacturing and thus need to be understood by all the manufacturers.

Also, using conventional statistical process controls in industries, variable parameters are not monitored in real time and thus the need to assess the response ability of advanced LoA. In developing countries, cost of production of goods is unfriendly due to adoption of conventional manufacturing processes and this has led to unsustainability and collapse of local industries. In Kenya, sugar industry is an example where companies are collapsing, and this calls for drastic measures. Four elements in this study were considered to demonstrate the performance of process in the sugar industry namely: real-time monitoring, product quality, resource utilization and production rate. These are in line with the expected competitive production.

By implementing and simulating the integration of lean and level of automation, this research will assess the technical importance of adopting improved manufacturing processes through lean automation. In addition, the research will draw on a case sugar industry firm employing automation to identify the drivers and obstacles behind competitive trend. Consequently, the dynamic capabilities of automated manufacturing systems will be considered.

1.1.5. Sugar industry in Kenya

According to KSB (2007), Kenyan sugar factories are high cost producers of sugar which has led to its reduced competitiveness compared to the same industry in other countries. The cost of sugar production in Kenya is twice the cost of production in other competing COMESA countries currently estimated at USD 870 per MT. This is relatively high compared to Zambia (USD 400), Sudan (USD 340), Swaziland (USD340), Malawi (USD 350) and Zimbabwe (USD

300) (Kenya National Assembly, 2015). Also, the sugar factories are affected by low production rates, unpredicted harvesting schedules, debts, managerial incompetency, fluctuating weather patterns, process and equipment wastages and obsolete technology. The factories continue to operate at low capacities due to low levels of technical efficiency and wastages (KSI, 2009 and KSB, 2010).

The main determinant of the productivity of a sugar factory is the ratio of total sugar cane crushed to total sugar made (TC/TS ratio). This shows the MT of cane crushed to yield one MT of sugar. A comparison of TC/TS ratios between private and government owned factories reveals a significant difference. In 2012, the conversion rate for Butali was 9.74 while Chemelil was 18.41 (KSB, 2013). This means Chemelil had to crush an extra 9MT of cane to produce one MT of sugar like Butali. Being a member of COMESA free trade agreement, Kenya is bound by the provisions of the free trade protocol that allows sugar imports from COMESA FTA countries to gain access to the Kenyan market without any quota or duty restrictions. This has resulted in an influx of sugar imports whose prices are much lower in comparison to sugar produced in the country. This renders locally produced sugar non-competitive.

Based on this observations, it is evident that sugar industries in Kenya are not performing to the expected global competitive standard and therefore not sustainable. It is on this basis that the study is founded to investigate the impact of proper adoption of automation on the performance of these sugar industries in the presence of lean environment in Kenya.

1.1.6. Mumias Sugar Company Limited

Mumias Sugar Company which is located in Mumias town in Kakamega county of Kenya, was selected as the case study company. It is a local sugar industry which was founded in 1971 and has progressively upgraded its plant operations from semi-automatic to full automation in some work modules of its layout. It also has both the conventional and automatic juice extraction techniques in terms of modern mills and a diffuser. The different process lines, incorporating different levels of automation within the factory, provided an opportunity to set up experiments for the various levels of automation to ascertain the impact of various levels of automation on the process performance.

According to Wachira (2014) and Wanga (2014), Mumias Sugar Company Limited is the largest sugar manufacturing company in East African with a production capacity of about 250,000 MT accounting for 42% of the estimated 600,000 MT annual national output. The company has its operation center located in Nairobi, the capital city of Kenya. The raw materials which is sugar cane is obtained from both the company nuclear estate (7%) and outgrowers (93% consisting of over 50,000 registered farmers with over 99,000 acres (MSCL, 2012). The company's ownership is by the following shareholdings: Government of Kenya (20%), Standard Chartered Nominee Account KE17984 (2.31%) Kenya Commercial Bank (1.72%), Jubilee insurance(1.46%), Abdul Karim Popat (0.94%), Suresh Varsani (0.6%), Pradeep Patani (0.59%), Yana Trading Limited (0.56%), Ramila Mavji and Harji Mavji Kerai (0.49%), CfC Stanbic Nominee Account R57601 (0.45%), Other Investors via NSE (70.89%) (Mburu, 2014)

According to MSCL (2012), the sugar production process consists of the following stages in a sequential order:

- Cane handling - where the cane is stored in the cane yard to provide stock for the factory to crush throughout. The cane is offloaded using hydro unloaders and overhead gantry cranes from trucks onto the feed tables then conveyed to the main cane carrier.

- Cane preparation - where cane is finely broken into small grains before juice extraction by either milling or diffusion. This increases surface area for juice extraction. Preparations are done by passing the cane through one or two sets of knives and then to the shredder. Preparation index (PI) gives an indication of the extent to which cane cells have been split by knives and shredder relative to the stack.
- Juice extraction - this is the removal of juice from the crashed cane fibres by diffusion or mill tandems. Diffusion is the washing of the pol out of the prepared cane fibres at high temperature of about 85^{o}C, compared to mills which involves mechanical squeezing of the juice out of the fibres. Upon washing, fibre residue called bagasse is conveyed via dewatering mills for drying then used as fuel in the boilers to generate steam, A diffuser is 60m long and 6m wide enclosed box with perforated bed that has a chain that drags prepared cane slowly as water and juice percolates through the bed.
- Juice treatment - where the juice from the diffuser is weighed as a factory control measure then heated to elevate the temperatures for the next process of clarification.
- Juice clarification - involves liming of juice to coagulate, form and remove insoluble matter. Flocculants are also added to the limed juice to facilitate settling of this matter.
- Juice evaporation - where clear juice is concentrated from 11% brix to 63% brix by removal of water. Usually, 1 kg of steam evaporates 1 kg of water from juice. However, if 1 kg of steam is fed to the first vessel with a quadruple effect evaporator (four vessels) then it will evaporate four kilos of water
- Sugar boiling - Is the saturation of sugar crystals into highly concentrated sugar solutions in three steps using three different boiling system. The supersaturation coefficient of

solution is a measure that indicates the extent to which a solution is over saturated. This over saturation is what forces sucrose to be deposited onto the crystals making them grow.

- Crystallization-Crystallizers are stirred tanks in which massecuite is allowed to cool, thus effecting further crystal growth as the sucrose in the mother liquor is exhausted. The purity of the liquid fraction (mother liquor) of the massecuite is called the nutsch purity. Monitoring the nutsch purity is an important way of measuring the performance of crystallizers
- Centrifugation - A centrifugal separates mother liquor from the crystals in a massecuite. Continuous centrifugal are normally not used to produce VHP sugars
- Sugar drying - to maintain keeping and handling qualities, VHP sugars are dried from a moisture content of 5% to 0.1%
- Bagging/packaging is done using clean food grade materials. Sugar is bagged/packaged to protect it from contamination. This is done in 50kg, 2kg, 1kg, 1/2kg, and 1/4kg.

Figure 1-1: Pre-milling section at Mumias Sugar Company Ltd (MSCL, 2012)

1.2. Problem statement

According to Ondiek and Kisome (2013), sugar industries in Kenya operate on conventional automation for monitoring and controlling processes among other challenges. This automation technology is inefficient and has recorded uncompetitive and unsustainable process performance leading to collapse of Kenyan sugar companies. Consequently, proper sensitization of lean automation and its impact on the performance of industrial competitiveness of sugar industry in Kenya is non-existence. They revealed that in Kenya, sugar companies exhibited either partial application of lean techniques or improper consideration of automation. In their conclusion, there is no understanding of lean and automation principles and therefore little benefits have been realized. They recommended a need to investigate the effects of advanced techniques like lean automation, for full benefits.

In addition, Maria (2015) observed that fluctuating demand for sugar exports and their declining production is on a rise yet major sugar industries derive the advantage of being automated. With automation we expect better process performance and subsequently high production. Can this be attributed to improper determination of level of automation required at the respective stages of the process flow?

Therefore, a proper integration between lean techniques and optimum level of automation to have lean automation, its adoption and implementation was investigated on process flow to assess its effects on performance. Possibly, effective process performance in sugar industry will be realized when lean approach is applied fully prior to appropriate selective automation. Thus, the need to assess the effects of lean automation on process performance.

1.3. Objectives

1.3.1 Main objective

To establish the impact of lean automation as an advanced manufacturing technique on process performance in sugar industries in Kenya.

1.3.2 Specific objectives

a. To evaluate the impact of advanced levels of automation on adaptive control for improved real time process control to reduce process variations in sugar industry
b. To assess the potential of advanced levels of automation on improving production quality.
c. To assess the effect of advanced levels of automation in minimization of resource wastage.
d. To indicate the effect of advanced levels of automation on continuous improvement in sugar industries.

1.4. Justification

To be the strongest competitor, a company should manufacture the most number of parts within the shortest time and lowest costs. In many cases, this can be through adopting lean manufacturing methods like continuous improvements. But this alone will not help the industry to forecast and monitor the trends in technology and demand in the market, gauge their competitive viability, create scenario reports and sensitivity analysis (Chen, 2010). Thus depending on the method and level upon which automation has been adopted, lean manufacturing can impact on flexibility of automation and shortened cycle time of design for assembly and quality function deployment (Orr, 1997).

Effective lean manufacturing combines both manual and automation to obtain the right type of automation. The concern for engineers is to identify what should and what should not be automated. It was found that LoA 4 (conventional automation) and lower automation levels do not perform well in a lean manufacturing system because the loading and transfer of parts cannot easily be achieved by operators, making it reasonable to incur the expenses of investing in LoA 5 and 6 (Hedelind et.al, 2008). It also has lower changeover times and inadequate uptimes than level 5 and 6, since it uses simple and special purpose machines. The higher automation levels are flexible and has a potential to address the inadequacies of LoA 4 (Harris and Harris, 2008; Mehrabi, 2002). One concern during employment of lean manufacturing is the conformity of traditional automation to the techniques and principles of lean. Thus, the term lean automation. This is the proper integration of automation into the techniques and principles of lean manufacturing. That is, choosing the appropriate level of automation (Jackson et al., 2011).

With these expectations of lean automation, the firm may achieve zero inventory, shorter product cycles and improved quality. Many industries noted that quality control was achieved easily with automation than human-based. Lean automation also minimizes capital outlays related to waste and inventory. This is a result of absolutely investing the capital in the automation of equipment, process and product (Orr, 1997).Thus, the need to establish the impact of lean automation on process performance.

Adding together what all researchers believe, many organizations adopted lean manufacturing methods to ensure competitiveness through technology trends. Lean philosophy helps to ease automation of a company due to increased quality and short cycle times. Lean automation can employ both automatic and manual principles. However, it first need to adopt automation onto the practices and principles of lean manufacturing. Lean automation can then be described as the approach of applying the optimum quantity of *smart* on a task and can be utilized for faster product, lower inventory levels, simplifying operation processes, increasing turnover rates, improving quality and maximizing the reliability of equipment.

1.5. Significance of the study

The findings of this study will be applied for decision-making process by the management of sugar companies as well as state organs for policy formulation in realization of a sustainable and competitive sugar industry in the country. This is in line with the tenets of both Kenya's vision 2030 and UN country ranking (2015), where Kenya is among the developing countries that needs the adoption of new technologies to boost her industrial economy. Also, the Kenya's vision 2030 envisions to attain a competitive industrial economy free of any wastes with a GDP of 20% compared to the current 10% (Kenya National Bureau of statistics, 2015).

To the sugar industry practitioners, lean automation will enhance the repair and maintenance of processes since they can incorporate maintenance programs like predictive, preventive and total productive maintenance. This will in turn maximize reliability of lean automated equipment and continuous improvement by the trained staff. Through the use of reliable equipment and robustness, lean automation will minimize over-complicated practices. This will ease configuration, enhance visual inspection and reduced cycle times. Some of the key-enablers in the Lean Robotics which are vital for future robotic working cells are: increased ease-of-use, intuitive user interfaces, and better ways to visualize what is going on in the cell and focus on simplicity and usability (Hedelind et al., 2008a).

The study will also add value to the existing knowledge on adoption of advanced manufacturing techniques like lean automation which is a new technique in the sugar industry.

Lean Automation aims at improving cost effective methods in the production line. Leanness does not necessarily mean lowest investment cost, but the total investment cost will be lower compared with the traditional route because all matters are “on the table” from the beginning and all eventualities are considered (Hollingum, 1994). Harris and Harris (2008) stated that a manufacturer of lean equipment should have a knowledge in machine design and prospects of different types of automation. The knowledge will help in achieving flexibility and efficiency in the manufacturing process. Lean manufacturing is implemented to enhance flow while automation is chosen and integrated into that flow to improve it. Thus, the optimum level of automation is crucial.

1.6. Scope

The research focused on the pre-milling (juice extraction) section in a case study sugar industry with an automated production line that will be simulated for lean outcomes and level of automation. The focus on juice extraction alone is guided by the fact that, the output sugar production is directly proportional to the quality and quantity of the juice extracted. Therefore, conclusions drawn on the juice extraction can be extrapolated to significantly apply to the overall sugar production by the process line. Thus, the experiment was only conducted on the process line of pre-milling section which comprises of cane handling, cane preparation and juice extraction stages. The parameters attributed to lean automation were subjected at every stage of this section and the findings extrapolated to the overall performance of sugar production process with lean automation adopted.

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive review of lean manufacturing, automation adoption, process performance in sugar industries and the fit between them. The review concentrates on the literature of the link between level of automation and process performance and the influence of lean manufacturing indicators to this relationship. This chapter also provides a means of setting the scope of the current research, as well as to identify the gaps that this research seeks to address. A framework is then proposed for incorporating lean manufacturing indicators in the relation between level of automation and process performance. This framework poses the hypotheses arising out of the reviewed literature.

2.2 Theoretical framework

In manufacturing, process improvement is vital in modifying and transforming raw materials into final product. In response, Western companies adopted crucial changes to their operations, by mimicking the JIT (just-in-time) and adoption of TQM (total quality management) processes adopted by the likes of Toyota (Westkämpfer et al., 2011). In this study, the intention was to investigate the impact of integration of level of automation and lean manufacturing on the process performance in sugar industries in Kenya. Thus, the research was guided by three theories namely: six sigma, lean manufacturing and theory of constraints (TOC). These theories are in agreement with the lean manufacturing indicators adopted in this study to enable incorporation of the levels of automation.

2.2.1 Six - sigma theory

Six Sigma theory emphasizes on reduction of variations to enhance processes. Through the help of statistical techniques, it is possible to forecast the process outcomes. If unexpected outcome is noticed, then advanced control tools can be used to explain the phenomenon. In relation to lean automation, the integration of lean and proper levels of automation provides a suitable advanced control tool to best understand and identify parameters that affect or vary the process, and hence the overall performance of the organization (Dave, 2002).

2.2.2 Lean manufacturing theory

Lean manufacturing emphasizes on waste reduction. Waste is anything that hinders high production and process capabilities like machine set ups. In this regard lean emphasizes on smooth and continuous flow with little waste along the process line. Womack et al. (1990) found that competitive markets such as lean manufacturing that are aimed at saving cost have influenced many industries like motor industry especially Toyota. Lean manufacturing focuses on the reduction of waste in terms of scrap, manpower, high inventory and work in process, process complexity, improper space utilization, high investment on equipment among others. Jackson et al. (2011) asserts that the adoption of lean techniques has often enhanced competitive process performance in industries. In addition, industries can adopt advanced technology like automation to further improve manufacturing competitiveness.

2.2.3 Theory of constraints (TOC)

Theory of Constrains focuses on system improvement. A system is a combination of interrelated and dependent work cells which aim at attaining a common goal. Any weak cell will become the constraint along the process line and will hinder the expected outcome. In this respect, TOC identifies those constraints that slow the process flow. By improving each work cell independently, increased overall performance can be realized that will maximize the output of the industry (Dave, 2002).

2.3 Lean Manufacturing and Sugarcane Extraction process

As attributed to Padraic (2010) waste is that which is bought but not utilized. Sustainable manufacturing denotes the adoption of manufacturing process that decreases negative impacts on the environment, improves energy and resource conservations, provide safety and are economical in operation. On the other hand, competitiveness is the ability of a company to efficiently and effectively produce goods more than its competitors. The competitive indicators include the rate of exportation, the market share of the company and its profitability. Sustainability is the bottom line in the achievement of social, environmental and economic performance. These two core values are lacking in our key local sugar industries, thereby initiating the need to undertake this study. The study will propose alternative technology for the sugar company for increased throughputs.

According to Oliverio et.al (2015), juice extraction in Sugarcane is a process operation where the water and sugars in the cane are extracted, and it occurs after cane preparation stages. Basically there are two techniques employed commercially to achieve this prior to cane preparation namely: mechanical squeezing, which employs mill tandems, or by diffusion where the prepared cane fibers are washed in many stages as the sugar contents and water are subsequently dissolved and sucked in a diffuser from the unbroken fibers constituting 10% and by leaching in broken fibers constituting 90%. The major concern during extraction process is the production of quality juice and final removal of the bagasse with the least moisture content of at least 50% of moisture, which can support burning in the boilers to produce steam and power. The goal is to extract the maximum mass amount of sugar contents in the cane fibers and consequently produce bagasse with optimum moisture content suitable as biomass fuel in steam or power boilers.

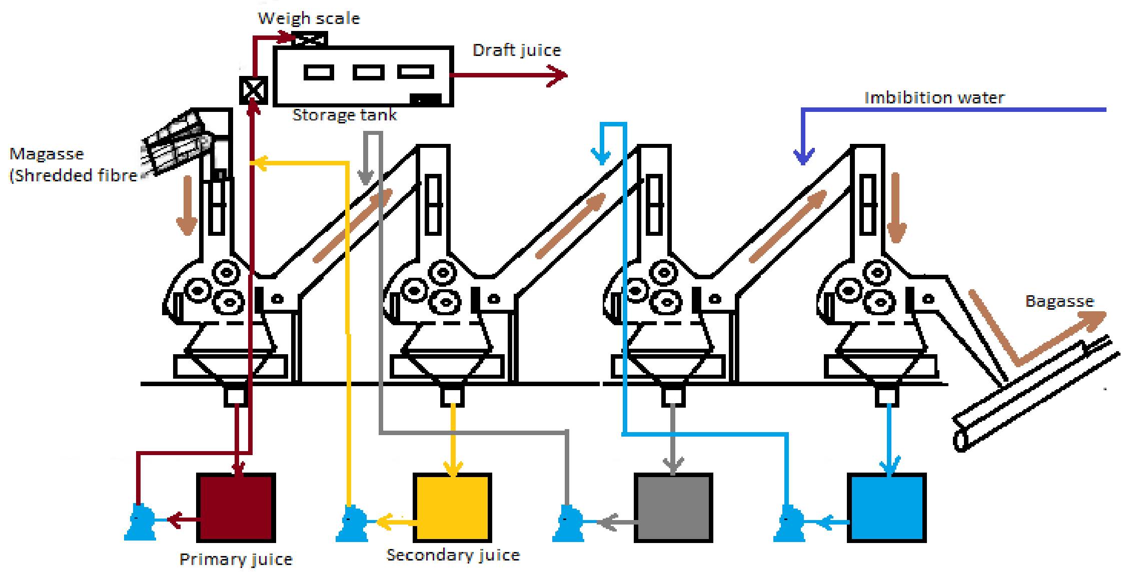

Figure 2-1: Arrangement of 6 sets of 3-roll crusher mills forming a milling tandem (Source: Oliverio et.al, 2015)

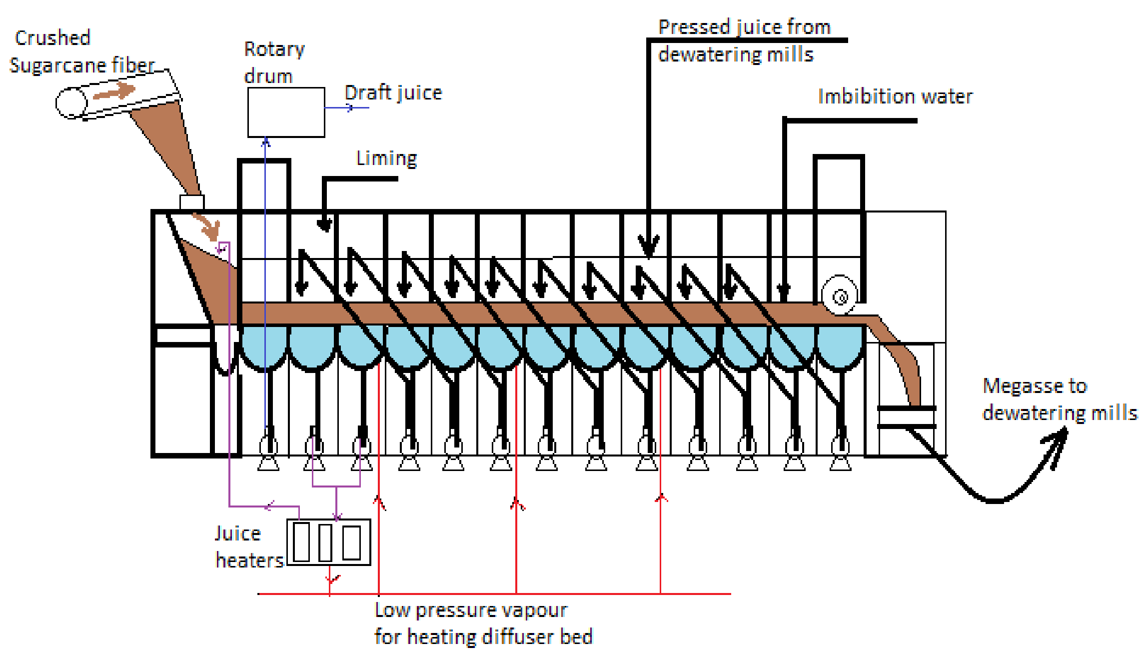

Figure 2-2: Complete juice extraction system by diffusion – cane diffuser (Source: Oliverio et.al, 2015)

2.3.1 Technical comparison: milling and diffusers

Following the main goal of the juice extraction process, the industry should select wisely the optimum technique to adopt for optimum production. In comparison, the factors in considering the viability and impact of any of the two techniques includes the frequency and quality of maintenance required, quality of juice extracts and power consumptions. Ideally, mill tandems are subject to severe wear during their operation and this subsequently affects the average extraction rates, compared to diffusers. However, extraction rates by diffusers are more sensitive to impurities caused by vegetable minerals present in the cane feedstock (Oliverio et.al, 2015)

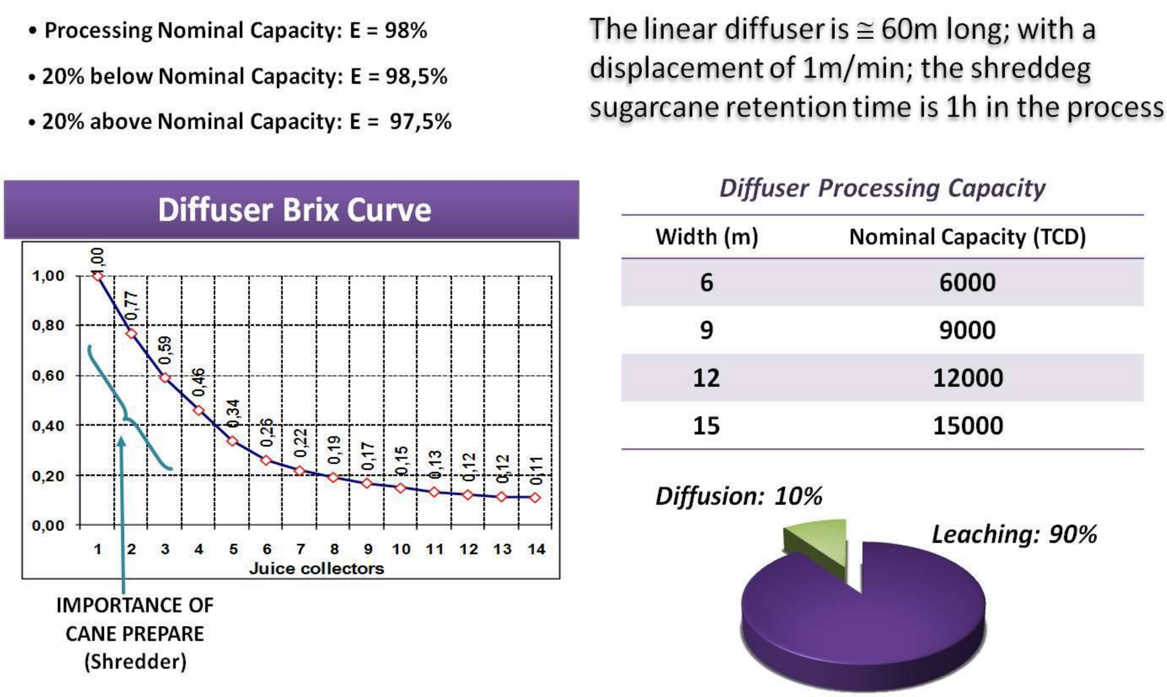

Figure 2-3: Typical diffuser extraction parameters (Source: Oliverio et.al, 2015)

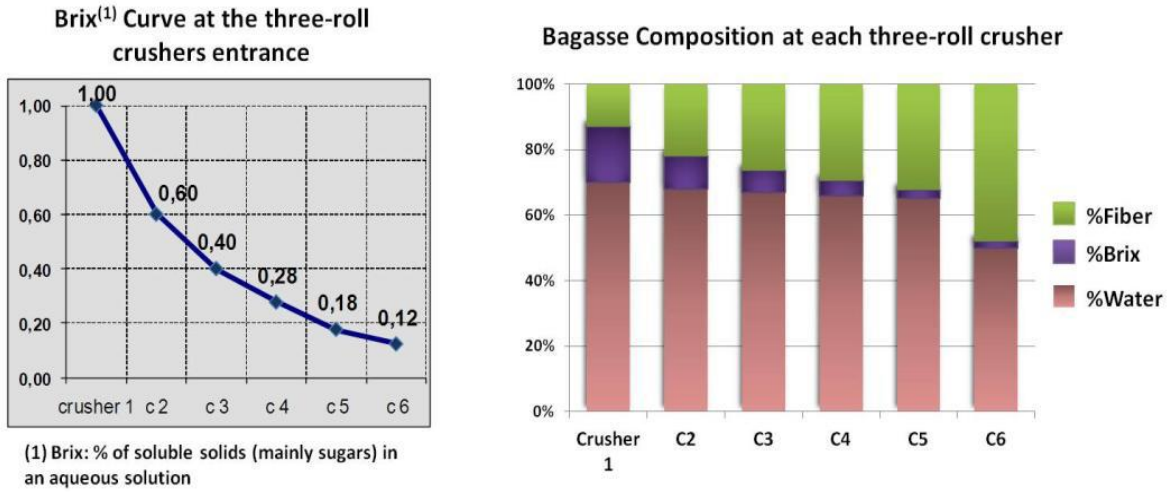

Figure 2-4: Typical extraction parameters in mill tandems (Source: Oliverio et.al, 2015)

2.3.2 Response time in a production system

The basic criterion of performance in a production system is response time. In ordinary production processes, the response time is measured in the range of five to ten millisecond. Thus, the response time in a process is reasonable if it is at its lowest value to demonstrate the rapid rate at which an anomaly can be detected by the system and appropriate action taken.

In a case of the computer processor, to check whether the performance of a CICS® system is in line with the system's required capability, then investigations should be on the hardware, the software, and the applications that are in the installation. However, response time depends on the speed of the processor, and on the nature of the application being run on the production system. Thus the shorter the response time, the more rapid a process will be executed in a production system. Also, to note is the consistency of the response times. Sharp variations will imply erroneous system operation. (Colledani, 2006).

Also, Gambier (2004) asserted that, the correctness of an output in a real-time monitoring system does not only depend on the logical accuracy of the calculation but also on the time at which the output is displayed. According to Gambier (2004), this assertion validates the importance of time factor for a real time setup in any manufacturing and industrial system, and that there exist timing constraints which will always hinder cycle times of manufacturing tasks. As a result, these tasks must be able to synchronize with the real-time events in the external environment within the industry. Therefore, a real-time setup must synchronize with the external events associated with it.

2.3.3 Influence of pH and temperature on the sugar production process

According to Panpae et.al (2008), the rate of sucrose inversion in sugar cane juice extraction is largely depended on the solid content, temperature and pH. When these parameters are increased, they equally increase sucrose inversion rate. To lower the total reducing sugar, temperature control is important in regulating the sucrose inversion while a high pH in the OH^- from lime slightly affects the properties of the juice extract in comparison to the high apparent purity of the pure sugarcane juice. It was observed that at 80°C, sugars and %pol magnitudes were relatively significant compared to lower temperatures. However, when solid content was increased at 80°C, it recorded a lower %pol which is the sucrose content. Therefore, juice extraction process is highly depended on the pH and temperature fluctuations, which must then be maintained for optimum production.

According to Day J.M (1996), most sugar mills implement pH control technique via feedback loop relaying a mA electric signal to an actuator valve or pump for corrective reagent delivery into the process line. The usual technique in conventional automation consists only a proportional control instead of a more complex PID control. The proportional control is only possible because sugar processing is an operation which requires an appropriate recipe. The cane feed stock often exhibits small variabilities in acidity or alkalinity. In most sugar industries in developing countries, pH monitoring and control is absolutely manual where samples are manually scooped from mills for pH measurements at intervals without precise electronic pH sensing techniques. In some mills, pH is measured using pH papers. The only challenge in monitoring pH in sugar mills is getting an accurate equipment with the ability to withstand the harsh conditions within this environment.

pH sensors must be appropriately located and installed due to two reasons. First, the sensor must visualize the process fluid in real time without experiencing any time lags. This must be at the operating flow rate, pressure and temperature. Because temperature change affects pH and chemical reactions in the process fluid, it is therefore, necessary that pH measurements are taken upon reagent addition and resulting reaction at process operating temperatures.

2.3.4 Preparation index

This requires an additional set of mechanisms to further split the fibres. Therefore the need of a shredder and high density knives. It may be thought of an additional power consumption to the plant, but if low power and variable speed controlled electro mechanical shredders and high density knives are chosen, the advantages of high preparation index and high extraction of juice will be attained. This is in line with Kent and Lewinski (2007) who observed that for efficient cane preparation, the method of preparation index provides better result than the pol-in-open cells method. Also, advanced In-line shredders can easily be incorporated even when processing whole-stick cane and the power consumption is relatively less with a single shredder than with two sets of knives and a shredder as it is in the case of conventional automation.

2.3.5 Effect of pol and brix on sucrose content

According to Xiao (2017) in his analysis of sugar cane juice quality indexes it was found out that, the effect of polarization (%Pol) and %brix on sucrose content is directly proportional to the apparent purity of the juice. Further, sucrose content is the quotient of %pol to %brix, thus it increases as the %pol increases and decreases as the %brix increases. This subsequently influences the effect of apparent purity and %brix on the sucrose content while maintaining %pol in that, sucrose content decreases with an increase in apparent purity and %brix.

In addition, this conforms to Six Sigma theory that emphasizes on reduction of variations to enhance processes. Through the help of statistical techniques, it is possible to forecast the process outcomes. If unexpected outcome is noticed, then advanced control tools can be used to explain the phenomenon. In relation to lean automation, the integration of lean and proper levels of automation provides a suitable advanced control tool to best understand and identify parameters that affect or vary the process, and hence the overall performance of the organization (Dave, 2002).

2.3.6 Power transmission and set up time

Kent and Lewinski (2007), explored the comparison between electromechanical mill tandems and the conventional drive (turbine). The electromechanical mill drive has the following merits: higher efficiency and speed ranges, better speed control, easier monitoring, higher torque range and lower maintenance cost. Further, a comparison between variable speed electromechanical drives and electro-hydraulic drives in relation to efficiency and torque – speed was also determined and the following was deduced:

- Electro-hydraulic drives have a better torque – speed advantage.

- Both electromechanical and electro-hydraulic drives have the same efficiencies in similar applications
- The efficiency of a hydraulic drive is relatively easy to measure compared to that of electromechanical (VFD) drive.
- Power losses and service factor must be considered when determining the efficiency of the drives.

It was observed that, the efficiency of the variable frequency electromechanical drive is of higher than the electro-hydraulic drive.

Also, Ali et.al 2011, confirmed that productivity is related to value adding activities in the manufacturing transformation process. Thus, any activity not adding value is regarded as a waste. It is therefore, essential to minimize these resource wastes if productivity is to improve. This is in line with the theory of waste elimination which emphasizes on the reduction of non-value adding activities.

2.3.7 Impact of pH and temperature optimization in minimizing sucrose losses in sugar industry

Panpae (2008) reviewed that, the main objective of perfecting industrial processes is to maximize production capacities while upholding continuous improvement of product quality and minimizing production costs. Thus, there is always a tradeoff between these requirements. This majorly is the case when high quality sugar production at minimized invert sugar is the requirement from the sugar factory. The sugar cane is first crushed so that the juice can be extracted. The crushing breaks up the hard nodes and flatten the stems to expose the fibers. The juice extract collected is filtered and treated, then boiled to remove excess water. During juice treatment, filtration of the juice should be done through a cloth before boiling so as to eliminate any solids particles in the cane. Lime ($CaOH_2$) is then added before boiling to neutralize the juice. After heating, the juice is passed onto the pans which are normally stirred rapidly to provide for an even crystallization and incorporation of air. The output sugar production should correspond to a brix (sugar content) of 90-95% when incorporating simple sugar measuring instruments. However, the main challenge that needs to be addressed is on accurate, precise and real time monitoring of total reducing sugar (reducing sugars plus hydrolyzed sucrose) which is very crucial in the provision of performance data and information to help evaluate the raw material and quality control in sugar manufacturing processes. It was also observed by Day (1996) that pH, temperature and response time monitoring is a vital task to undertake in a sugar industry so as to uphold the optimum required sugar quality by facilitating sucrose reduction.

2.3.8 Continuous improvement

Oliverio (2013) alluded that the juice extraction can reach only up to 80% with mill tandems, but can be higher when a diffuser incorporated with dewatering mills are used. In relation to lean automation, Six sigma emphasizes that the integration of lean and proper levels of automation will provide a suitable advanced control tool to best understand and identify parameters that affect or vary the process, and hence the overall performance of the organizations. Also, Ali et.al (2011) conforms to this finding through his study that to attain a continuous improvement, advanced manufacturing techniques like automation should be in place together with lean philosophy that will enable elimination of waste and efficient utilization of resources.

The current study considered the above mentioned process performance factors that affect quality sugar production in line with lean thinking as follows: Adaptive control (response time, process temperature and the process pH), production quality (brix, pol and Preparation Index), waste reduction (power consumption, set up time and the process cycle time) and continuous improvement (rate of production)

2.4 Lean manufacturing and industrial process performance

As reviewed by Naveen et.al (2013), lean manufacturing is a technique known by many industrial set ups (Womack & Jones, 1994), it emphasizes on waste elimination in a process line (Womak & Jones, 1996). The waste can be termed as an intangible or tangible activity along the process line that don't add value to the finished goods or services. Though, for lean manufacturing, the essence is to produce as per the customers' requirement, it necessitates appropriate elimination of these wastes in the process line (Henderson and Larco, 2003). Since lean is an operational culture that will initiate an organizational change, it is vital first to enlighten the employees on the action that will be taken and the expected outcomes before the adoption of lean techniques. Otherwise resistance to change may arise and cause hindrance to effective production (Csokasy & Parent, 2007, Bhasin & Burcher, 2006). The essence being to achieve high performance efficiency in the processes (Holweg, 2007). According to Huang et.al (2013), proper implementation to lean can result to reduction, if not elimination, of waste such as high inventory and delayed material handling. Consequently it will realize low production cost.

As reviewed by Shaman and Sanjiv (2013), implementation of lean manufacturing is directly allied to the performance of industrial processes. Currently, the quality of a product is judged by the customers' satisfaction, which can only be achieved when the process line is excellent, that is, free from any waste. The waste elimination can only be achieved through lean thinking. The combination of SWOT (strength, weakness, opportunity, threats) analysis and lean techniques in an industry will further enhance the waste elimination (Upadhye, Deshmukh, &

Garg, 2010). If well implemented, all the waste will be eliminated, the cycle time will reduce, the work in process and inventory will be low, productivity will be high and ultimately he production cost will be low(Seth & Gupta, 2005; Dennis, 2007).

As attributed to Zafarzadeh (2013), emphasize should be concentrated on the smooth flow of those activities that only add value. In line with the customers' expectations, production departments should only work on the subsequent operation that is yet to take place within the shortest time possible. Therefore, continuous improvement of the process line is important since we are interested in reducing the time that will be taken from the order placement to the product collection. Time reduction can only be a reality if non value adding activities are eliminated (Liker, 2004, p20).

Lean which is implemented majorly by Just in time (JIT) technique focuses on waste elimination. This implies adoption of minimal manpower, space, investment in equipment and tool, lead times, inventory and manufacturing defects among others. This reciprocates well with Just in time implementation which aims at improving quantity, inventory, and lead times cycles, investment cost, staff welfare and workforce productivity (Fullerton and McWatters, 2001). In lean, strength is aimed at eliminating the above parameters to attain infinite variations in production and zero wastage (White et al., 1999; Womack et al., 1990). Therefore, lean automation is applied to achieve waste elimination and value creation for customers (Hedelind and Jackson, 2008b, Jackson et al., 2011). Importantly, lean is about waste avoidance. In Japanese waste is called *muda*, which is any activity that utilizes inputs but doesn't create any outcomes. The efficiency of a lean organization is realized when inputs are spent on productive activities. Though there is a challenge in identifying these activities (Orr, 1997).

Lean is also perceived in terms of the organization of the production line. In this, teams of workers are organized and led by team leaders and not a foreman as it's the case in mass production. The workers will effectively effect the tasks allocated (Womack et al., 1990). This will create satisfaction and fulfilment due to the workers not being confined to repetitive tasks. These teams have the authority to stop a production line where necessary in case of a breakdown repair. Full participation by workers is practiced through the provision to suggest on enhancing continuous improvement. The continuous improvement technique, a Japanese word for *keizen* is effective since proper motivation to workers who understand the processes well can substantially contribute immensely (Ribeiro and Barata, 2011). In manufacturing, inventory reduction is also a focus. Thus, warehouses and buffers are eliminated since they are a form of waste that is costly. The essence is to manufacture a product when only needed or an order if it is placed. This calls for a highly synchronized network of the industry, clients and suppliers. In this matter all efforts are going to avoid wasteful product stock (Kochan, 1998).

By and of itself, lean depends on personal responsibility and customer satisfaction to the level which customer specifies (Chen, 2010). Lean manufacturing is considered to be an enhancement of mass production, hence it is assumed not to be a new technique. Its objectives are to maximize profit by reducing costs and waste of material and improving quality, in such a way one can say these are essentially the underlying principles of mass production (Mehrabi, 2002). To enhance reduced inventory, just in time (JIT) a Japanese word for *kanban,* is the philosophy that can achieve smooth supply chain flow of parts. This will facilitate manufacture of what is needed without waste and subsequently reduced waste.

JIT is only a tool for lean manufacturing. Therefore lean combines *muda, keizen* and *kanban.* The impact of a properly structured JIT will be to eliminate storage facilities that add to the cost of the product (Ribeiro and Barata, 2011). However, lean also has adverse influences on innovative capabilities, product design, work characteristics and employee outcome (Chen, 2010). According to White et.al (1999), success of JIT is when employees are fully involved in the continuous process improvement this will in turn enhance a competitive advantage than those companies that do not practice it. This is only possible if the company's organizational structure and culture are conducive and flexible to allow for positive changes (Ribeiro and Barata, 2011; Hedelind and Jackson, 2008b; Jackson et al., 2011).

Therefore, lean emphasizes on achieving supremacy through continuous improvement, reducing inventories, reducing waste and creating value for end-user customers. Lean has proved to reduce production cost, increase quality and productivity, reduce lead times, eliminate inventory and enhance employee welfare in areas it has been employed. Unlike in industries where it is yet to be implemented. While it is verified that lean manufacturing has been effectively implemented, it can have adverse influences on the company if it is not well-balanced with automation.

As reviewed by Zafarzadeh (2013), a check list for assessing production changes that will lead to lean manufacturing is shown in Table 2.1. To achieve lean production, the indicators should change as shown under the behavior column.

Table 2-1: Lean manufacturing indicators' behavior (Martinez et.al, 2001)

Approach	Indicators	Behavior
Removal of non-value activities	Frequency and distance products are conveyed	Decreases
	Ratio of similar parts produced in the industry	Increases
	Cost of work-in-progress relative to sales	Decreases
	Inventory variations	Increases
	Quantity of time required for task altered	decreases
	Ratio of preventive maintenance to total productive maintenance	Increases
Continuous Improvement	Number of proposals per worker in a year	increases
	Ratio of executed proposals	Increases
	Convertible and/or paybacks from the proposals	Increases
	Ratio of inspection conducted by manufacture personnel	Increases
	Ratio of defective parts attuned in manufacturing	Increases
	time machines are upended because of breakdown	Decreases
	Cost of rework and scrap relative to sales	Decreases
	Workers devoted majorly to quality control	decreases
Multifunctional team	Ratio of workers operating in teams	increases
	Quantity and ratio of tasks achieved by workers	Increases
	Ratio of workers changing tasks in the company	Increases
	Typical occurrence of job rotation	Increases
	Ratio of team leaders nominated by their team workmates	Increases

JIT manufacturing and Supply	Lead times of clients' order	Decreases
	Ratio of products supplied JIT	increases
	Integration level between supplier delivery and the firm's Manufacturing data structure	Increases
	Ratio of JIT supply between divisions in the manufacturing path	Increases
	Production and delivery lot sizes	Decreases
Incorporation of Suppliers	Ratio of products co-designed by the supplier	increases
	Number of proposals prepared to supplier	Increases
	Rate of visits to the firm by dealer’s technicians	Increases
	The frequency of visits to industry’s suppliers by technicians	Increases
	Ratio of documents exchanged via Intranet	Increases
	Average time cycle agreement for important supplies	Increases
	Average number of suppliers for crucial spare parts supply	Decreases
Flexible information System	Frequency of conveying information to the workforce	increases
	Frequency of top administration meetings with staff	Increases
	Ratio of procedures written and documented by the industry	Increases
	Ratio of manufacturing equipment which are computer integrated	Increases
	Number of assessments personnel can accomplish with no supervisory control	increases

2.5 Automation adoption on process performance

Automation can be regarded as either fully automated or full manual, and it is aimed at acquisition of value addition, better process throughputs and increased productivity. (Winroth et al., 2006; Orr, 1997). In reference to Delkhosh (2013), due to technological advancement, automation was initiated in manufacturing industries. Flexible equipment can work tirelessly for repeatable tasks. This improves efficiency and subsequently the competitiveness of the industry (Winroth et al., 2006; Säfsten et al., 2007).

Similarly, the competitive approach of reducing the unit cost of a product agitated the need for a faster production pace, and this is through automation of crucial tasks (Ribeiro and Barata, 2011). In addition, there are extreme ordinary situations where human intervention is impractical and thus calls for the implementation of automation. (Harris and Harris, 2008). Examples are hazardous products, sensitive nanotechnology components, accuracy, high tolerance components and strenuous activities. Therefore, automation provides an excellent ergonomics (Kochan, 1998).

A number of factors are important to consider when designing competitive production systems. These include changes in: customization, integrated information systems, rapid changeability, robustness, level of automation, flexibility in terms of changeovers, production volume, and product variants.

Industries that aim at reaping the full advantage of automation must first enlighten the employees to avoid resistance to change, and these new implementations should be gradual and stepwise (Orr, 1997). Automation is regarded as a key to transformation in an industry, whose goal is to reduce production cost. This is demonstrated in the automotive industry which has recorded tremendous improvement in lowering the cost of production through less dependency on human labour (Jovane et al., 2003). Industrial robots have been incorporated to substitute human in performing labour intensive activities and in unsuitable environments (Hedelind et.al, 2008; Jackson et al., 2011).

Automation can further be advanced to achieve product design within the shortest time possible and increase the productivity, and this leads to reduced costs and increased volume outputs. These are as a result of appropriate process control through planning methods and manufacturing tool selection that is provided by automation (Orr, 1997).

On the contrary, automation is considered not to be suitable in the following cases: when ramping up manufacturing of new products, manufacturing of a large variety of products and variants in small volumes, very short product life cycle and requisites of product e.g. visual inspection (Winroth et al., 2006).

Decisions about automation are made on the basis of the following important factors: desired product quality, conduciveness of work environment and rationalization. Product quality is associated to the customer perspective, the work environment is concerned with the internal perspective while rationalization can be described as the shareholder perspective (Lindström et al., 2006). Kaplan & Atkinson argued that automation offers reliability and permits flexibility through virtually eliminating setups or change over times. Goldhar et.al (1986), Hansen et.al (1997) and Hoque (2000) suggested that through automation sustainability and competitiveness can be assured, and this can increase process performance.

The best of automation efforts are realized if they only conform to the industry’s goals and objectives. The main key to success is to integrate good organizational structure and manufacturing tools (Winroth et al., 2006). If the main goal is to reduce production cost, then the concern will only be to automate with a mere implementation strategy on human labour such as task allocation. Otherwise, if the aim is to achieve advanced manufacturing technology, then automation will mainly focus on long term technological solutions for the company with no regard to implication on human force. In this regard, a proper balance of an optimum level of automation will apply in the task allocation (Säfsten et al., 2007).

The tasks are separated into two categories, information and control tasks and mechanical tasks. Some companies talk about semi-automation, which often is referred to the humans performing some tasks, such as changing work piece or pushing the button to start each operation (Winroth et al., 2006). Groover (2000) elaborates that, automation is the accomplishment of a task without human intervention. It is assigned using a program of commands integrated with a control system that executes the commands.

For optimum technological solutions, an integration of automatic and manual functions of a manufacturing plant to have semi-automatic processes will result into efficient monitoring and control of both physical and statistical quantities that affect the processes. This integration will result to the so called level of automation that ranges from purely manual to fully automated process operations. Choosing an optimum level of automation will have a positive outcome on the manufacturing process, contrary to if automation is under or over applied (Säfsten et al., 2007).

2.5.1 Levels of automation

According to Harris and Harris (2008), there exist five levels of automation in manufacturing. Level 1 consist of pure manual tasks by an operator, that is manual loading and starting of a machine, cycling or operation, unloading and finally transferring the machined part to the next manufacturing stage like in a manual press. In level 2 the loading onto the machine is done manually by an operator, followed by an automatic machine cycling or operation, the manual unloading and transfer of the machined part to the next manufacturing stage. In level 3 the loading is done manually by the operator, next the machine cycles automatically, same to unloading of the part from the machine. Finally, the part is transferred manually by the operator to the next stage. In level 4, the part is loaded automatically, followed by automatic machine cycling, automatic unloading and finally manual transfer to the subsequent production stage. Level 5 is fully automatic, that is loading and cycling, unloading and transfer of parts are all automated.

The gap between level 3 and level 4 is great. This gap is in terms of equipment cost, cost of maintenance and ergonomic costs among others. A shift to level 4 implies an increase in cost and decrease in flexibility. A third level machine operates with 95% uptime, yet fourth level operates at 70-75% uptime while level 5 operates at 65-70% uptime. As the process is more automated the uptime decreases gradually. This gap can also be in terms of changeover time which is shorter in Levels 1, 2 and 3 than it is in levels 4 and 5. This makes the upper levels of automation to have a desirable change over cycle rate called takt time. However, when the takt time is low, tasks will be accomplished easily due to less inventories in the industry, thus the three lower levels of automation are suitable (Harris and Harris, 2008).

When level 5 machine is employed to achieve production, it is common that an engineer and a technician must be hired to maintain that machine. Thus, if individual machines performing specific functions are implemented by a company with the optimum level of automation, there will be flexibility, faster change over and quick uptime. The parameter to compete in the industry is to be flexible rather than just implementing automation design for future demands which can change anytime (Harris and Harris, 2008).

Another model for work functions was developed by Sheridan and where LoA was classified as LoA 1 (with work functions totally manual) to LoA 10 (with work functions totally automatic) and these are grouped into two major activities namely: mechanized tasks and computerized tasks. Classifications of manufacturing systems is based on the kind of operation, type of layout, automation level and part or product variety (Lindström et al., 2006).

Groover (2000) also proposed three automation levels and three different layout. This was obtained from the learning rate curves plotted for different types of work. Three control and automation levels comprises system positioning, production system and machine tool. Five possible levels of automation in a production plant can be identified as the device automation, Machine automation, Cell automation, Plant automation and organizational automation. Level 2 encompasses automation of individual machine tools like PLC, CNC, industrial robots and computerized controllers. The material handling equipment represents technologies at level 2, although some of the handling equipment is sophisticated. In all these levels, the working environment should be properly selected.

According to Garcia (2015), the following are the sigma levels for control monitoring:

- 5 to 6s: Six Sigma automated process is autonomously designed to monitor and automatically eliminate or adjust any error condition with no human intervention.
- 4 to 5s: the automatic process will shut down the operation in case of an error and prevent any further activities until the necessary action is undertaken.
- 3 to 4s: error detection will prevent a part from moving to the next stage on a production line.
- 2 to 3s: statistical process control on dependent variables with their cause are spotted and amended by trained operators in line with the rules and regulations.

- 1 to 2s: statistical process control on independent variables are spotted and corrected by operators.
- 0 to 1s: design of process audits and statistical operational plans through training programs

In summary, automation enhances efficiency, quality and reduces cost of production. It permits much greater manufacturing flexibility, that is, products which have larger volumes or ergonomically awkward to manipulate can be produced in an easy way. Since automation focuses on problems related to human engineering, then it is important to observe level of automation between the human being and the equipment. There are a lot of classifications of level of automation between researchers from five-levels of Harris's classification to three levels of Groover's classification. Meanwhile, the best level which could be called "rightomation" may be Semi-Automation.

2.5.2 Automation Challenges

Orr (1997) observed that low capital per unit and low complexity resulted when a mass production system was automated. This is because a new product cannot be introduced on an existing process line unless the line is redesigned or completely replaced. Thus in mass production, machine changeovers also need to be automated. Similarly, the equipment involved are customized or specialized and thus can cause increased equipment cost.

Winroth et.al (2007) reported that the most important barriers for automation are technical feasibility, education and qualification, and economic viability. Other problems are: adapting the product to automation, the high number of different products and variants, problems to get the money back from the investment and the lack of competence at shop floor level. In the vaster view, he investigated that automation is never related to the production capabilities, the equipment are too complicated and challenges occur when trying to balance manual approach along the process line. Work in process cost will then be increased by the huge buffers which will adversely increase the cost. This implies that automation is challenging if not well related to the expected long term production strategies (Winroth et al., 2006, Winroth et al., 2007).

Frohm et.al (2006) found that automation involves more complex production processes while in more advanced automation, it includes investment cost. This makes it challenging too in machining and manufacturing. Automation is also not suitable if it is applied to newly introduced products, short term products or short product life cycles. Equally variations in the production is challenging to automation. On the contrary, high volumes of production and ergonomics problems cannot be addressed manually. However, as manufacturing becomes more complex as demand for specialized parts increase, higher levels of automation will record undesirable outcomes. It is affirmed that a variation in product and adapting the products for automated production can be a problem. In their findings, some firms mentioned untimely automation planning or operator training and also, a challenge in getting payback from automation. Most industries admit that operator's competence is the main issue when automating activities involving seasonal products. This results to high changeover times and cost-inefficiency (Frohm et al., 2006).

Hedelind et al. (2008) believes that lack of flexibility could be considered as a challenge to automation. The flexibility of a manufacturing system can be defined and determined by its sensitivity to change and serves as a measure for a number of variant products in a production system. A flexible system is that which can accommodate changes effectively at a low cost within a manufacturing system. Lack of re-configurability could be another challenge to the automation which is defined as a systems' response to changes. The main barriers to small industries in investments in industrial robotics are cost and the need for expertise and experience.

Hedelind et al. (2008) asserts that automation is accomplished by complexity. Many reasons have also hindered the adoption of industrial robots including scarcity of robotic cells, lack of understanding of robotic technology by the operator which creates uncomfortable environment and a lot of protocols that needs to be followed yet they don't give information on procedures. Other challenges include fear to invest in automation when there is variation of products, shorter cycle times, high costs, failure to consider advanced manufacturing techniques and the need to hire maintenance engineers and technicians, configuration and flexibility costs. However, sophisticated machines could give interference due to fixed solutions and limited transparency into the automated process (Jackson et al., 2011).

Hedelind et al. (2011) noted that there are many detailed and specific challenges that any firm may be encountered as such the small buffers between stations may cause stops in one station and affect other stations too. The times of set ups in the stations may be another challenge, but the observation noticed was the availability of a wide range of automation solutions in the industry. This was because various suppliers and system integrators were utilized without any detailed technical specifications provided from the company. In the same category, there was also low confidence in the ability of the operators employed by the company to resolve issues arising in the automated stations (Hedelind and Jackson, 2011).

2.6 Modelling of experiments

According to Tzu-Ming et.al (2001), two major models can be used for experimental analysis namely: Regression models and ANOVA models.

a) For regression models, independent variable y is

$$y = \eta(x, \vartheta) + \varepsilon \qquad \textit{2-1}$$

Where x represents a set of dependent experimental conditions,

$\vartheta \left(\vartheta_1 \dots \dots . \vartheta_p\right)^T$ Represents a vector of unknown parameters,

ε =represents an observational error, a random variable.

$$\eta(x, \vartheta) = f_1(x)\vartheta_1 + \dots + f_p(x)\vartheta_p \qquad \textit{2-2}$$

That is

$$y = f(x)^T \vartheta + \varepsilon \qquad \textit{2-3}$$

Where

$$f(x)^T = \left(f_1(x), \dots \dots ., f_p(x)\right), \vartheta = \left(\begin{pmatrix} \vartheta_1 \\ \vdots \\ \vartheta_p \end{pmatrix}\right) \qquad \textit{2-4}$$

Or in matrix notation (to include all observations)

$$Y = X\vartheta + \vartheta \qquad \textit{2-5}$$

b) Analysis of variables (ANOVA)

The variance of a model is gotten by the sum of the square deviations from the mean.

$$Var(y) = \sum_j \left(y_j - \bar{y}\right)^2 \quad \text{2-6}$$

Where $\bar{y}$ is the mean of the model y

For any model M that forecasts values $\hat{\bar{y}}$ for the data, the residual variance or residual sum of squares of M is evaluated in the same way as:

$$RSS_M(\boldsymbol{y}) = \sum_j \left(y_j - \hat{\bar{y}}_j\right)^2 \quad \text{2-7}$$

Therefore, if more than single variables are involved then ANOVA is the appropriate model that behaves like a multi regression model for nonlinear variables as:

$$y_j = \eta\left(x_j, \vartheta\right) + \varepsilon_j \quad \text{2-8}$$

Taylor series expansion of the model, at a priorϑ^o, yields

$$\eta(x,\vartheta) = \eta(x,\vartheta^o) + f^T(x,\vartheta^o)(\vartheta - \vartheta^o) + (\vartheta - \vartheta^o)^T f_{..}(x,\vartheta^o)(\vartheta - \vartheta^o) + .. \quad \text{2-9}$$

Where

$$f^T(x,\vartheta^o) = \left(\frac{\partial\eta(x,\vartheta)}{\partial\vartheta_1}, \frac{\partial\eta(x,\vartheta)}{\partial\vartheta_2}, \dots, \frac{\partial\eta(x,\vartheta)}{\partial\vartheta_p}\right) I_{\vartheta=\vartheta^o} \quad \text{2-10}$$

And $f_{..}(x,\vartheta^o)$ is a matrix of second order derivatives with respect to the parameters, thus a sumarised linear model being

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + a_i + b_{i1} X_1 + b_{i2} X_2 + b_{i3} X_3 + \varepsilon \quad \text{2-11}$$

Where $a_i, b_{i1}, b_{i2}, b_{i3}$ are jointly normal multivariate with zero mean and some unknown covariance matrix M.

In this study, ANOVA modelling will be adopted due to its ability to handle multivariate problems with nonlinear variables.

2.7 Summary of Research gap

Competitive industries adopt cost saving strategies like lean manufacturing. In others, stiff competition and challenges like poor ergonomics and quality, and high labour costs initiate industries to adopt higher levels of automation. Most lean manufacturers allege that too much automation due to lower levels of automation result to much complexity that even contradicts lean principles. Some don't have confidence in the automation facilities and are left to rely on their suppliers and contributors. Automation requires high investment costs, maintenance and complex interface, specialized training and space utilization among others (Delkhosh, 2012). With these challenges of low levels of automation, it is important to implement just in time before automating. This is because automation aims at increasing improvements on quality and lead times. Thus, it should not be of concern as to whether lean is manual or fully automated, since it can integrate both manual and integrated tasks. Therefore, it's key to determine the optimum level of automation in a lean environment to obtain lean automation benefits (Granlund et al, 2011; Harris, 2008; Hedelined et.al, 2011; Orr 1997). A chronological summary of the research gaps to be explored in the study is summarized herein in Table 2-2.

Table 2-2: Chronological summary of the research gaps

Author	Objective	Methodology	Findings	Gap
Day, 1996	pH Control in the Sugar Mill	Survey conducted with survey questionnaires	- In most sugar industries in developing countries, pH monitoring and control is absolutely manual where samples are manually scooped from mills for pH measurements at intervals or pH papers - Severe variability in pH level.	Need for smart technology to reduce variability in pH.

Orr, 1997	Impact of automation in the Australian and Asian industries	Survey conducted with survey questionnaires	- low capital per unit and low complexity resulted when a mass production system was automated - increased equipment cost	Need to determine the optimum automation level in a lean environment
Winroth et al., 2006	Requirements and existing theory of automation in manufacturing	Survey conducted with survey questionnaires	- Automation is never related to the production capabilities, the equipment are too complicated and challenges occur when trying to balance manual approach along the process line. - Work in process cost increased by the huge buffers which adversely increase the cost. - automation is challenging if not well related to the expected long term production strategies	Need to determine the optimum automation level in a lean environment
Frohm et al., 2006	Impact of Automation in Manufacturing	Survey conducted with survey questionnaires	- In lean environments, if automation is not well planned, it may cause challenges ranging from maintenance, difficulties in visualization, time consumption, and difficult machine-human interface	Need to determine the optimum automation level in a lean environment
Kent and Lewinski, 2007	comparison between electromechanic	Experimental	- the efficiency of the variable frequency	Need for advanced technology to

	al mill tandems (VSD) and the conventional drive (CSD)		electromechanical drive is higher than the constant electro-hydraulic drive	reduce resource wastage
Hedelind et al., 2008a	Impact of industrial robots in manufacturing firms	Survey conducted with survey questionnaires	- Automation is affected by lack of sensitivity to change, systems' response to changes and low confidence in the ability of the operators employed by the company to resolve issues arising in the automated stations	Need to determine the optimum automation level in a lean environment
Kenya Sugar Board Reports, 2007, 2009,2010, 2013	Statistics of Sugar Production in Kenya	Review of audit reports and survey questionnaires	- Kenyan sugar factories are high cost producers of sugar currently estimated at USD 870 per MT. - The factories operate at low capacities due to low levels of technical efficiency and high resource wastages	Need for adoption of advanced techniques in sugar production in Kenya
Ondiek and Kisome, 2013	Adoption of Lean Manufacturing Tools and Techniques in Sugar Processing Industries in Kenya	Survey conducted with survey questionnaires	- In Kenya, sugar companies exhibited either partial application of lean techniques or improper consideration of the level of automation. - No understanding of lean manufacturing principles and therefore little	Need for a holistic integration of advanced techniques, like lean automation.

			benefits have been realized. - Undesirable process efficiencies and productivity with average sugar productivity of 85%, which is below 92% recommended world average.	
Oliverio et.al 2015	The technical comparison between Mills and Diffuser juice extraction systems in Brazil	Experiment was set, data recorded from each system employed	- Juice extraction can reach only up to 80% with mill tandems, but can be higher when a diffuser incorporated with dewatering mills are used.	Need to assess the impact of an optimally automated diffuser on quality juice production
Maria, 2015	A review of economic growth in Africa by the World bank	Survey conducted with survey questionnaires	- Fluctuating demand for sugar exports and their declining production is on a rise yet major sugar industries derive the advantage of being automated.	Need to integrate level of automation required at the respective stages of the process flow
Xiao et.al, 2017	analysis of sugar cane juice quality indexes	Experiment was set, data recorded from each system employed	- The effect of polarization (%Pol) and %brix on sucrose content is directly proportional to the apparent purity of the juice. - sucrose content decreases with an increase in apparent purity and %brix	Need for advanced technology to reduce variability in (%Pol) and %brix

2.8 Conceptual synergy

The three theories namely six sigma, lean manufacturing and theory of constraints are geared towards improving the process performance and they collaborate in terms of general criticisms on the cause of industrial failure. In addition, they make a few of the same assumptions. The emphasis on constraints by TOC, gives a clear indication at every stage of a production line to enhance improved output. This conforms to lean thinking where waste reduction is conducted to rectify the weak cell/modules with the aim of achieving increased outputs. Consequently, it conforms to six sigma in that when the weak cell is improved, there will be less process variations and this will improve quality. Ultimately, all the models derive at attaining improved quality and subsequently effective industrial performance.

2.9 Conceptual framework

All local sugar industries in Kenya, records a declining production trend. In Kenya, all the industries are at the knee of closure if not uncompetitive and unsustainable production. This follows the proved inadequacy of advanced manufacturing approach among many other limitations that can foster a good process performance. The framework developed gave a conceptual basis for an experimental case study analysis. The framework links lean automation integration and process performance with lean manufacturing to moderate the relationship. Lean automation was selectively chosen as the appropriate advanced manufacturing approach that suits the performance of sugar processing with the main objective of material handling and adaptive control.

Lean automation was examined in terms of level of automation (LoA) adoption in the sugar industries. Process performance was explored in terms of adaptive control, production quality, waste reduction and continuous improvement indices. Adaptive control was characterized by rapid changeability of response time, process temperature and process pH. Production quality was characterized by the flexibility of changeovers in %brix, %pol, preparation index (PI) and % apparent sugar quality. Resource utilization was characterized by waste reduction in power consumption, setup time and process cycle time. Continuous improvement was characterized by the variability in the rate of production. The chosen parameters of the process performance are those factors that directly affect production line and sugar quality.

The framework, poses an expectation that the higher the level of automation, the better the process performance. The framework also suggests that adoption of lean automation requires a lean manufacturing environment with an aim of value addition as shown in Figure 2-5 below.

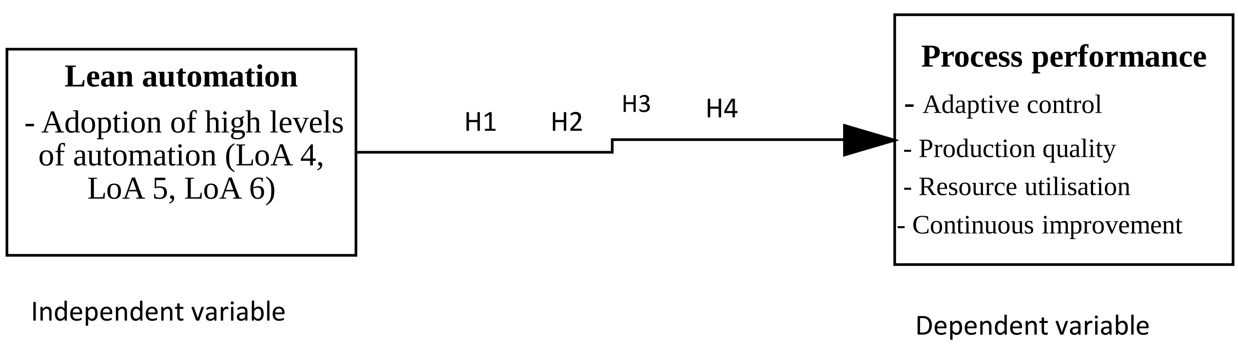

Figure 2-5: Conceptual framework (Source: Researcher)

2.10 Hypothesis

The competitiveness and sustainability of process performance in local sugar industries is on a decline due to adoption of obsolete technology among other factors. In this regard, there is need for an advanced manufacturing approach to address the production in the local industries. This prompted the necessity to assess the impact of lean automation on process performance in sugar industries guided by a null hypothesis (Ho) of there being no relationship between lean automation and process performance indicators. However, to validate the null hypothesis, the listed alternative hypotheses were tested in line with the process performance indicators.

a. $H1_0$: All the LoA means are equal for adaptive control parameters;

   $\mu_{LoA\,4} = \mu_{LoA\,5} = \mu_{LoA\,6}$

   $H1_1$: At least one of the LoA means is different from one of the other means for adaptive control parameters; $\mu_{LoA\,4} \neq \mu_{LoA\,5} \neq \mu_{LoA\,6}$

b. $H2_0$: All the LoA means are equal for resource utilization parameters;

   $\mu_{LoA\,4} = \mu_{LoA\,5} = \mu_{LoA\,6}$

   $H2_1$: At least one of the LoA means is different from one of the other means for resource utilization parameters; $\mu_{LoA\,4} \neq \mu_{LoA\,5} \neq \mu_{LoA\,6}$

c. $H3_0$: All the LoA means are equal for quality production parameters;

   $\mu_{LoA\,4} = \mu_{LoA\,5} = \mu_{LoA\,6}$

   $H3_1$: At least one of the LoA means is different from one of the other means for quality production parameters; $\mu_{LoA\,4} \neq \mu_{LoA\,5} \neq \mu_{LoA\,6}$

d. $H4_0$: All the LoA means are equal for continuous improvement parameters;

   $\mu_{LoA\,4} = \mu_{LoA\,5} = \mu_{LoA\,6}$

   $H4_1$: At least one of the LoA means is different from one of the other means for continuous improvement parameters; $\mu_{LoA\,4} \neq \mu_{LoA\,5} \neq \mu_{LoA\,6}$

CHAPTER 3 : MATERIALS AND METHODS

3.1 Introduction

In this chapter, the relevant materials and method aspects are discussed in line with the study objectives to assess the attainment of the expected outcome as highlighted in the conceptual framework. These include: experimental unit, materials used, research design, the experimental setups, measurement procedure, data collection tools, data analysis and validity and reliability of the data.

3.2 Experimental unit

Mumias Sugar Company, located in Mumias town in Kakamega county of Kenya, was selected as the case company. It is a local sugar industry that has progressively upgraded its plant operations from semi-automatic to full automation in some work modules of its layout. It also has both the conventional and automatic juice extraction techniques in terms of modern mills and a diffuser. This provided an opportunity to set up experiments for the various levels of automation to ascertain the impact of various levels of automation on the process performance.

3.3 Materials

1. Digital refractometer to measure directly Brix degrees or HFCS %
2. Stop watch
3. Visual display cameras and screens to provide high level of automation
4. Temperature sensor and probes provide high level of automation
5. SCADA platform provide high level of automation
6. DCI platform provide high level of automation
7. Polarimetre for measuring the %pol

3.4 Research philosophy

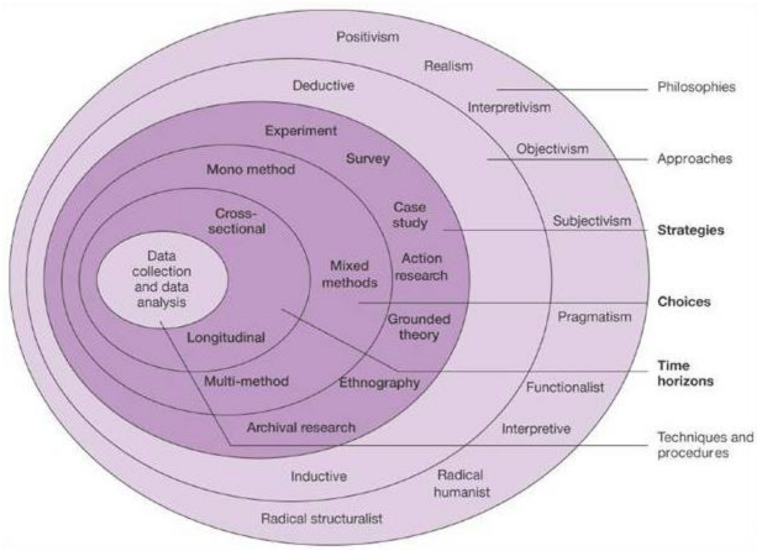

Figure 3-1: Research onion (Source: Saunders et al., 2009)

Saunders et al., (2009) suggested a research sphere to help guide researcher in choosing the best strategies and approaches given a scenario as shown in Fig 3.1. In the process of establishing knowledge on any subject matter, a researcher is guided by one of the many philosophical viewpoints as suggested by Saunders (2009) in the research union. The main philosophy that guides applied science is positivism. Positivism is based upon reason, truth and validity with a focus on facts that are gathered through direct observations and experience and measured empirically using quantitative methods of surveys and experiments and subjected to statistical analysis. In this philosophy the focus is on facts and looks for causality in the relationships through the formulation and testing of hypothesis.

The primary aim of this study was to experimentally inquire into the influence of level of automation on process performance hence characterized by the testing of hypothesis developed from existing theory (deductive approach) through measurement of observable process parameters. These parameters were measured experimentally using quantitative methods. The study therefore adopted a positivism philosophy, deductive approach and case study strategy which focused purely on facts, gathered through direct observation and measurements from the experiments.

3.5 Research design

According to Zafarzadeh (2013), the study into automation needs to be more clarified and established in a new and practical way. This called for an experimental design where a sample industrial case was reviewed to check the circumstances of real world for optimum lean outcomes and future benefits forecasted in collaboration with the appropriate level of automation adoption.

Therefore, a holistic single case design was chosen where the context was the case industry that practices automation, the case was lean automation, and the unit was the material handling modules of the pre-milling section. Case study will be chosen because of the following:

a. Research will entail "how" and "why" questions into the challenges and advantages of lean automation
b. Research hypothesis have descriptive nature
c. There are several bases of evidences like expert ideas around hypotheses, current data and state in the case industry and the present and future approach to automation progress.

Furthermore, case study approach was chosen as the study is an empirical investigation of a modern spectacle in its real-life perspective. Also, there is no clear boundary between automation and lean manufacturing in sugar industries, this created another motive for selecting this case study for this research. The parameters of manufacturing flexibility through lean automation and the production competitiveness was compared and the impact of lean automation assessed.

In summary:

- Case study approach with experimental design was chosen, and the experiment utilized the completely random design of experiment in analysis of variables.
- The parameters involved as per the appropriate categories included:
    - Treatments (parameters to be compared) - 3 treatments namely LoA4, LoA5 and LoA6
    - Experimental unit (where treatments are applied) – Case industry which is Mumias Sugar company Ltd
    - Responses (outcomes) – 4 responses that form indicators of process performance in sugar industry namely Adaptive control, waste reduction, quality production and continuous improvement
    - Randomization (to attain validity) – it was based on different process stage i.e P.Stage
    - Replication – it was attained by having 7 replicates
    - Measurement or response units (the actual objects or factors that affects the responses) – See *Figure 3-2* below**.**
    - Control treatment (standard treatment used as basis for comparison) - LoA 4

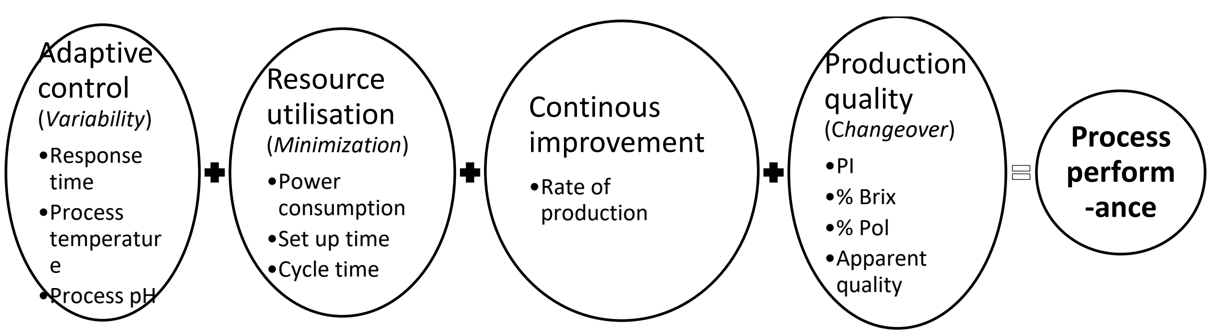

Figure 3-2: Cumulative responses contributing to process performance in sugar industry and their corresponding measurement units (Source: Author, 2019)

Table 3-1: Adopted matrix for the complete randomized design of experiment (Source: Author, 2019)

			PROCESS PERFORMANCE RESPONSES (y)										
			Adaptive Control **(y_1)**			Resource Utilisation **(y_2)**			Continous Improvement **(y_3)**	Production Quality **(y_4)**			
		P.Stage	Reponse Time **(y_{11})**	Process Temp **(y_{12})**	Proces pH **(y_{13})**	Power Consump **(y_{21})**	Setup Time **(y_{22})**	Cycle Time **(y_{23})**	Rate of Production **(y_{31})**	PI **(y_{41})**	~~%~~ Brix **(y_{42})**	% Pol **(y_{43})**	Apparent Purity **(y_{44})**
LEAN AUTOMATION TREATMENTS	LoA 4 (x_1)	WB	√	*	*	√	√	√	*	*	*	*	*
		CL	√	*	*	√	√	√	√	*	*	*	*
		FT	√	*	*	√	√	*	√	*	*	*	*
		KNIV	*	√	*	√	*	√	*	√	√	√	√
		SHREDD	*	√	*	√	*	√	*	√	√	√	√
		HDKNV	*	√	*	√	*	√	*	√	√	√	√
		EXTRACTN	*	√	√	√	*	√	√	*	√	√	√
	LoA 5 (x_2)	WB	√	*	*	√	√	√	*	*	*	*	*
		CL	√	*	*	√	√	√	√	*	*	*	*
		FT	√	*	*	√	√	*	√	*	*	*	*
		KNIV	*	√	*	√	*	√	*	√	√	√	√
		SHREDD	*	√	*	√	*	√	*	√	√	√	√
		HDKNV	*	√	*	√	*	√	*	√	√	√	√
		EXTRACTN	*	√	√	√	*	√	√	*	√	√	√
	LoA 6 (x_3)	WB	√	*	*	√	√	√	*	*	*	*	*
		CL	√	*	*	√	√	√	√	*	*	*	*
		FT	√	*	*	√	√	*	√	*	*	*	*
		KNIV	*	√	*	√	*	√	*	√	√	√	√
		SHREDD	*	√	*	√	*	√	*	√	√	√	√
		HDKNV	*	√	*	√	*	√	*	√	√	√	√
		EXTRACTN	*	√	√	√	*	√	√	*	√	√	√

Key: * = Non-applicable process stages (Empty fields)
√ = Applicable process stages for various process performance attributes

$$y_{11} = \beta_{011} + \beta_{111}\, x_1 + \beta_{211}\, x_2 + \beta_{311}\, x_3 + \varepsilon_{11} \qquad 3\text{-}1$$

$$y_{12} = \beta_{012} + \beta_{112}\, x_1 + \beta_{212}\, x_2 + \beta_{312}\, x_3 + \varepsilon_{12} \qquad 3\text{-}2$$

$$y_{13} = \beta_{013} + \beta_{113}\, x_1 + \beta_{213}\, x_2 + \beta_{313}\, x_3 + \varepsilon_{13} \qquad 3\text{-}3$$

$$y_{21} = \beta_{021} + \beta_{121}\, x_1 + \beta_{221}\, x_2 + \beta_{321}\, x_3 + \varepsilon_{21} \qquad 3\text{-}4$$

$$y_{22} = \beta_{022} + \beta_{122}\, x_1 + \beta_{222}\, x_2 + \beta_{322}\, x_3 + \varepsilon_{22} \qquad 3\text{-}5$$

$$y_{23} = \beta_{023} + \beta_{123}\, x_1 + \beta_{223}\, x_2 + \beta_{323}\, x_3 + \varepsilon_{23} \qquad 3\text{-}6$$

$$y_{31} = \beta_{031} + \beta_{131}\, x_1 + \beta_{231}\, x_2 + \beta_{331}\, x_3 + \varepsilon_{31} \qquad 3\text{-}7$$

$$y_{41} = \beta_{041} + \beta_{141}\, x_1 + \beta_{241}\, x_2 + \beta_{341}\, x_3 + \varepsilon_{41} \qquad 3\text{-}8$$

$$y_{42} = \beta_{042} + \beta_{142}\, x_1 + \beta_{242}\, x_2 + \beta_{342}\, x_3 + \varepsilon_{42} \qquad 3\text{-}9$$

$$y_{43} = \beta_{043} + \beta_{143}\, x_1 + \beta_{243}\, x_2 + \beta_{343}\, x_3 + \varepsilon_{43} \qquad 3\text{-}10$$

$$y_{44} = \beta_{044} + \beta_{144}\, x_1 + \beta_{244}\, x_2 + \beta_{344}\, x_3 + \varepsilon_{44} \qquad 3\text{-}11$$

Where:

β_{011}, β_{012}, β_{013}, β_{021}, β_{022}, β_{023}, β_{031}, β_{041}, β_{042}, β_{043}, β_{043} = corresponding population means

β_{111}, β_{211}, β_{311} ……………… β_{343}, β_{144}, β_{244}, β_{344} = coefficients of corresponding treatments

Also,

$$Adaptive\ control\ index\ (y_1) = \frac{2}{5}\left(\frac{\sum_1^3 y_{11}}{3}\right) + \frac{2}{5}\left(\frac{\sum_1^4 y_{12}}{4}\right) + \frac{1}{5} y_{13} \qquad 3\text{-}12$$

$$Resource\ utilization\ index\ (y_2) = \frac{2}{5}\left(\frac{\sum_1^7 y_{21}}{7}\right) + \frac{2}{5}\left(\frac{\sum_1^2 y_{22}}{2}\right) + \frac{1}{5}\left(\frac{\sum_1^6 y_{23}}{6}\right) \qquad 3\text{-}13$$

$$Production\ rate\ index\ (y_3) = \left(\frac{\sum_1^3 y_{31}}{3}\right) \qquad 3\text{-}14$$

$$Quality\ production\ index\ (y_4) = \frac{2}{5}\left(\frac{\sum_1^3 y_{41}}{3}\right) + \frac{3}{5}\left(\frac{\sum_1^4 y_{44}}{4}\right);\ \ y_{44} = \left(\frac{y_{43}}{y_{42}}\right) x100\% \qquad 3\text{-}15$$

Ultimately,

$$Process\ performance\ (y) = \left\{4\left(\frac{1}{y_1}\right) + 4\left(\frac{1}{y_2}\right) + \left(\frac{y_3}{4}\right) + \left(\frac{y_4}{4}\right)\right\} x100\% \qquad 3\text{-}16$$

3.6 Experimental set ups

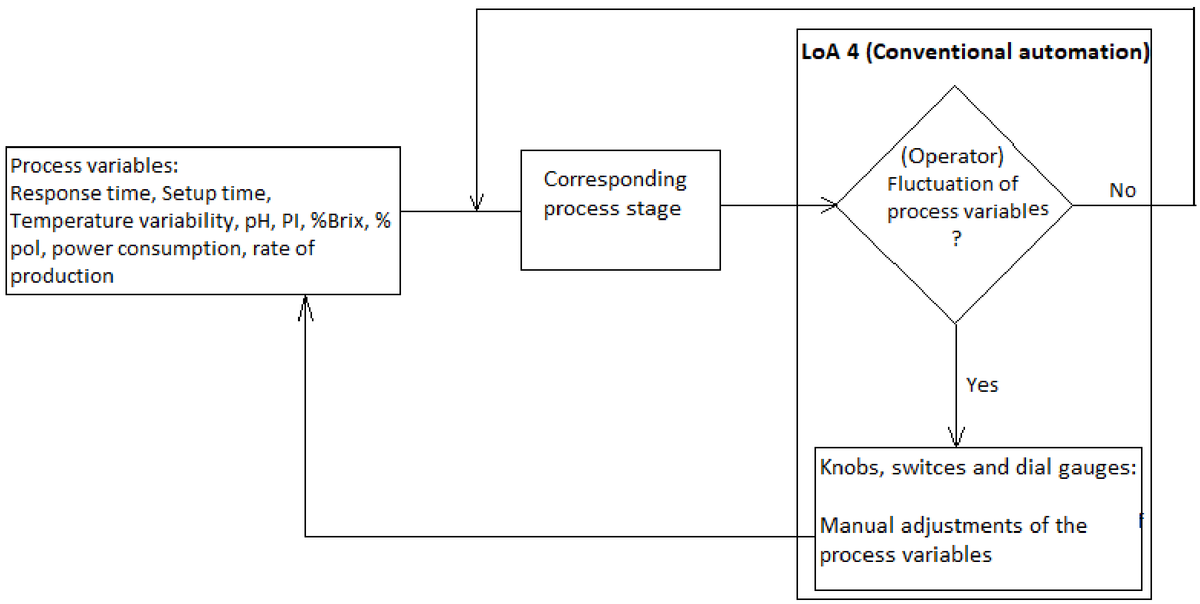

Figure 3-3 Experimental setup for Level 4 of automation (LoA 4) using control circuits

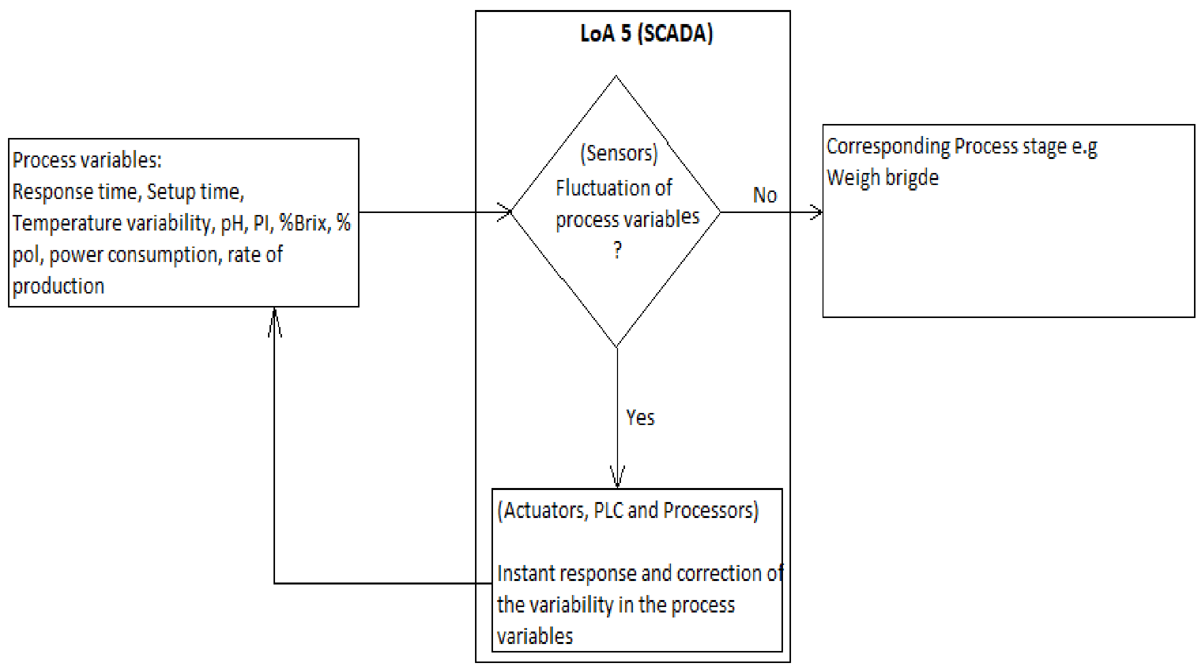

Figure 3-4 Experimental setup for Level 5 of automation (LoA 5) using SCADA

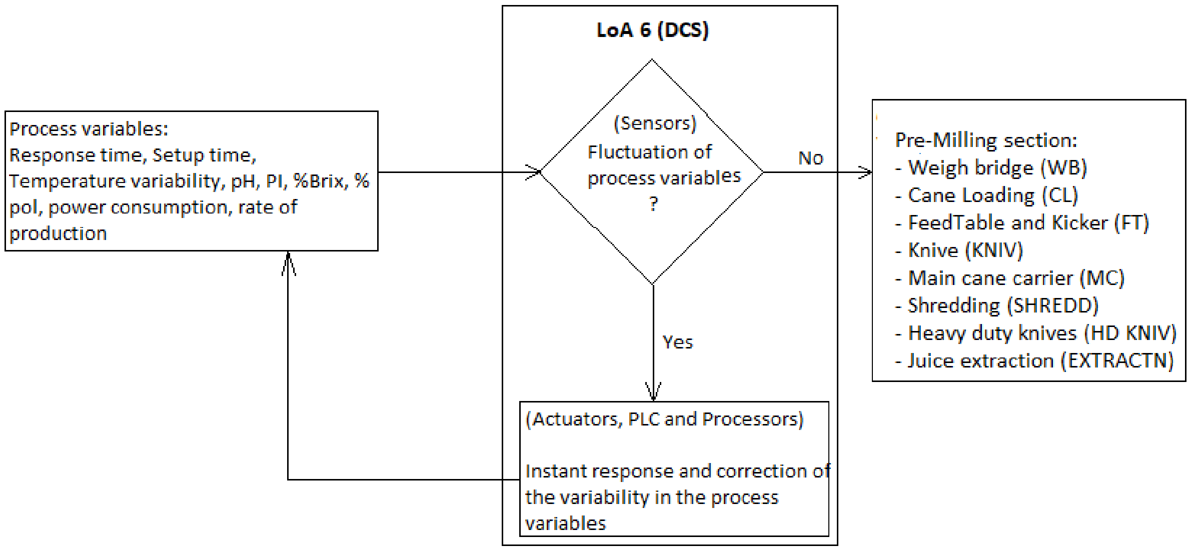

Figure 3-5 Experimental setup for Level 6 of automation (LoA 6) using DCS

3.7 Measurement procedure

1. The pre-process line was categorized into various process stages namely weigh bridge (WB), cane loading (CL), feed tables and kickers (FT), knives (KNIV), main cane carrier (MC), Shredder, heavy duty knives, shredded cane conveyor and juice extraction.
2. At each process stage, respective levels of automation were adopted through the different process lines and relevant parameters that affect the process were recorded. Level 4 was represented by the conventional process line which is common in all the local sugar industries while Levels 5 and 6 were represented by the new process line with automated mills and diffuser.
3. The three levels of automation namely 4, 5 and 6 were evaluated purposefully with level 4 being the conventional semi automation process technique that use control circuits and buttons employed by all the local sugar industries in Kenya.
4. Level 5 involved the use of SCADA system incorporated with autonomous independent machines within work cells.

5. Level 6 involved the use of DCS incorporated with autonomous independent machines within the entire plant or wide area.
6. Variability in %brix, %pol, temperature and pH were measured by the relevant instruments at the appropriate process stage.
7. Power consumption was measured from the cumulative power ratings of various machines over the operational time duration
8. Response time, cycle time and setup time were measured using a stop watch respectively
9. PI was measured from samples of cane fibers collected at intervals from the process line
10. The various levels of automation were defined by the following characteristics:

Level 4

- Open cell method of cane preparation
- Constant speed drive motors, compressor and pumps
- Stand-alone safety and operational control buttons
- Manual troubleshooting techniques of machinery (monitoring of process temperature, pipe and dust flow, mill processes)
- Random sampling of juice extract to monitor the quality of juice (temperature, brix, production rate)

Level 5

- Preparation index method of cane preparation (HD KNV)
- SCADA
- Variable speed drive motors, compressors and pump
- Autonomous diffuser and millers

- Automatic safety and operational controls
- Automatic troubleshooting
- Audio and visual process alert system
- Verification systems

Level 6

- DCS
- Variable speed drive motors, compressors and pump
- Autonomous diffuser and millers
- Automatic safety and operational controls
- Automatic troubleshooting
- Audio and visual process alert system
- Verification systems

11. The general procedure involved identification of lean automation prospects with the optimum level of automation and to design and simulate lean automation outcomes in 4 functionality domains meant to realize optimum process performance.
    - Reduction of non-value activities (wastages)
    - Continuous improvement
    - Real time monitoring
    - Quality production

3.8 Data collection

The following parameters that influenced the performance of the sugar process and the functionality of machineries were measured and recorded using various six sigma/lean techniques which include: Setup time Analysis, value stream mapping, Quality Data Collection and Analysis (Variability and Reject Rate reduction), Root Cause Analysis, semi structured interviews, simulations, observation:

- The power consumption of equipment and machinery at every process stage
- The preparation index (PI) at the knives, shredders and heavy knives
- The rate of feeding cane and juice extraction (production rate)
- The pol and brix (sugar concentration) of the sugar juice extract
- Change over time for each level at every process stage (mill settings, namely Mean circumference, Mill ratio and Set opening
- Cycle time for each level at every process stage
- Process temperatures variability from the expected optimum value
- Response time to a fault for each level at every process stage
- Effectiveness of control to the process
- Effectiveness of process pH detection and control to the process

3.9 Data analysis

By the help of software programs (Excel ™ and Minitab™), the collected data was analysed systematically using tables, statistics and graphs. The correlation of lean automation (independent variable) was established against process performance indicators (dependent variables) respectively using waste minimization index (moderating variable), to examine the strength of relationship of the variables for a sustainable and competitive industry. Using graphs and tables of those variables, the optimum level of automation was realised to provide lean production. Hypothesis testing was done using F-test since it is the most appropriate tool for the purposes of comparison of variables. It was expected to obtain the optimum potentials of lean automation indicator in minimizing lead time wastage, improving quality, increasing rate of production and rapid response.

3.10 Validity and Reliability of data

Validity was achieved through the vast data collection methods proposed for verification of the responses from the various sources. To have consistent results for this research, the design was selected as case study since it investigated a phenomenon from new insight relative to the existing models. Attributing to Zafarzadeh (2013), the significance of case study technique in logistics and creation of novel theory from insufficient philosophy. Also, the case design proposed was the holistic single case study, and this according to Yin (1997), is effective for this research since it's often used where it delineates a critical or distinctive situation.

Contrariwise, a single case can be opted since it's typical or supplies us with a possibility to detect and analyze an occurrence that has been considered afore. Concerning data-collection techniques, semi-structured interviews were used to enable a discovery of a broader insight to the matter, and the specialists interviewed were the reliable source for achieving accurate facts. Also, the experiment was meant to provide a control platform for comparison of results, hence Pearson's coefficient of correlation was used to validate the results obtained. This was to make the outcome dependable and valid owing to accuracy of the design and the fact that, all the data was attained from real prevailing organization and through examination with specialists. Value stream mapping was employed to authenticate interview verdicts that was to form a reliable instrument for detecting faults in a company.

CHAPTER 4 : RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter entails the analysis and discussion of experimental findings and evaluation. It gives findings and explains how level of automation as the indicator for independent variable affects the key indicators of process performance viz: adaptive control, production quality, waste reduction and continuous improvement. The results obtained were from each process stage and addressed each of the four objectives of the study as discussed.

4.2 Impact of lean automation on adaptive control for improved real time process control

In this objective, the impact of lean automation was analyzed based on its ability to improve on the adaptive real time control of processes. The lean automation was accomplished through the integration of three different levels of automation in a lean system of sugar production. Based on IEEE POSIX Standard (Portable Operation System Interface for Computer Environments), a real-time system is one in which the correctness of a result not only depends on the logical correctness of the calculation but also upon the time at which the result is made available (Gambier, 2004). Also, Gambier (2004) asserted that, the correctness of an output in a real-time monitoring system does not only depend on the logical accuracy of the calculation but also on the time at which the output is displayed. According to Gambier (2004), this assertion validates the importance of time factor for a real time setup in any manufacturing and industrial system, and that there exist timing constraints which will always hinder cycle times of manufacturing tasks. As a result, these tasks must be able to synchronize with the real-time events in the external environment within the industry. Therefore, a real-time setup must synchronize with the external events associated with it.

From Fig 2-1, on key indicators, it is noted that the effectiveness of an automated lean technique to provide real time monitoring is subject to the response time and process parameter variability within the system. The lower the response time and variability in process parameters, the better the performance of the level of automation in enhancing real time monitoring of the manufacturing process and vice versa.

In this experiment, adaptive real time control was demonstrated by three variables that were measured at the respective stages of the sugar pre-process line for different levels of automation. They included: response time to anomaly, process temperature variability and the process pH variability. The rate at which the anomaly was corrected and the variability in process parameters when using different levels of automation were analyzed to ascertain the level of automation that will give the best adaptive control, and whether it is dependent on the process stage.

4.2.1 Response time to anomaly

For the experiment conducted, the response times to anomaly for three different level of automation (LoA 4, LoA 5 and LoA 6) was taken in three process stages where it was applicable namely PS, CL and FT as shown in *Table 4-1* and *Figure 4-1*.

Table 4-1 Response time to anomaly for different LoA (Source: Field data, 2019)

		Response time (min)							
Stage	Level	1	2	3	4	5	6	7	**AVG**
	PS(LoA 4)	2	2.5	2	3	2.5	2	2.5	**2.4**
	PS(LoA 5)	0.5	0.6	0.5	0.8	0.5	0.6	0.5	**0.6**
PS	PS(LoA 6)	0.5	0.6	0.5	0.8	0.5	0.6	0.5	**0.6**
	CL(LoA 4)	4	4.5	4	5	6	4	5	**4.6**
	CL(LoA 5)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**0.5**
CL	CL(LoA 6)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**0.5**

	FT(LoA 4)	3	2	3	3	2.5	3	2.5	**2.7**
	FT(LoA 5)	0.5	0.5	0.5	0.5	0.5	0.5	0.5	**0.5**
FT	FT(LoA 6)	0.3	0.3	0.2	0.5	0.3	0.5	0.3	**0.3**

The above *Table 4-1* reveals that the conventional automation (LoA 4) at CL resulted to a low response time of 4 min (replicates 1, 3 and 6) and high response time of 6 min (replicate 5) for all the 8 replicates conducted, while both SCADA (LoA 5) and DCS (LoA 6) at CL recorded a low response time range of 0.5 min (replicate1-7) and high response time of 1 min (replicate 8). Similarly, at PS with conventional automation (LoA 4), a low response time of 2 min (replicate 1, 3, 6 and 8) and high response time of 3 min (replicate 4), while both SCADA (LoA 5) and DCS (LoA 6) at FT, recorded a low response time of 0.2 and min (replicate 1, 3, 5, 7) and a high response time of 1 min (replicate 8).

Also, at FT with conventional automation (LoA 4), the lowest response time was 2 min (replicate 2) and highest of 3 min (replicate 1, 3, 4, 6, 8). SCADA (LoA 5) recorded a constant and DCS (LoA 6) at FT recorded low response times of 0.5 min (all replicates) and 0.2 (replicate 3) respectively and a high response times of 0.5 min (replicate 8).

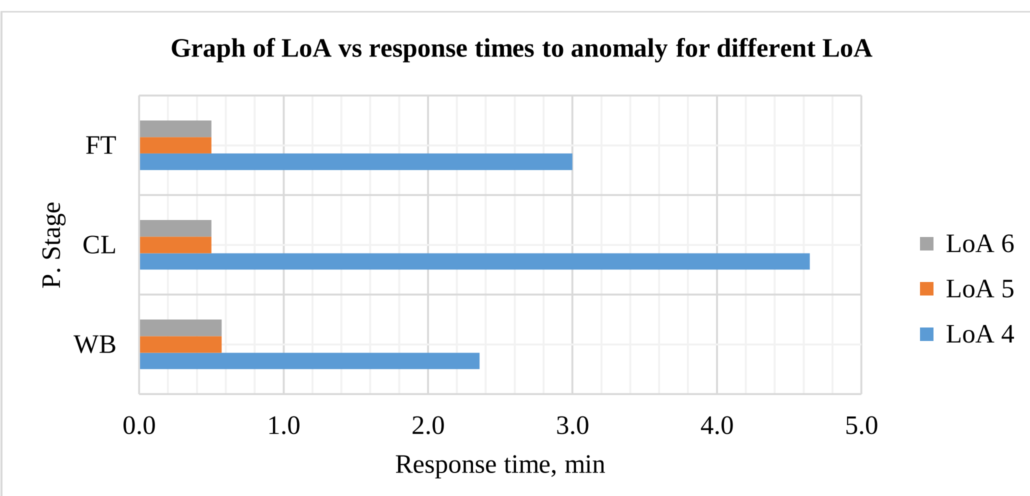

Figure 4-1: Graph of LoA vs response times to anomaly (Source: Field data, 2019)

From Figure *4-1*, LoA 4 has the highest mean response time of 2.4, 4.6 and 3 min at the PS, CL and FT respectively, as opposed to both LoA 5 and 6 that recorded the lowest mean response time of 0.6, 0.5 and 0.5 min at PS, CL and FT stages respectively. It is therefore evident that, the higher the level of automation the better the response to anomaly.

The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on process temperature variability. There were 7 replicates for each separate treatment levels under investigation.

Table 4-2 ANOVA for Response time to anomaly (min) versus LoA, P. Stage (Source: Field data, 2019)

Factor Information								
Factor	*Type*	*Levels*	*Values*					
LoA	Fixed	3	4, 5, 6					
P. Stage	Fixed	3	CL, FT, WB					
Analysis of Variance								
Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*F-Crit*
LoA	2	15.7868	85.00%	15.7868	7.8934	16.21	0.012	6.94
P. Stage	2	0.8379	4.51%	0.8379	0.4189	0.86	0.489	6.94
Error	4	1.9478	10.49%	1.9478	0.4870			
Total	8	18.5726	100.00%					
Model Summary								
S	*R-sq*	*R-sq(adj)*	*PRESS*	*R-sq(pred)*				
0.697826	89.51%	79.02%	9.86097	46.91%				
Coefficients								
Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*		
Constant	1.460	0.233	(0.814, 2.106)	6.28	0.003			
LoA								
4	1.873	0.329	(0.960, 2.786)	5.69	0.005	1.33		
5	-0.937	0.329	(-1.850, -0.023)	-2.85	0.047	1.33		
6	-0.937	0.329	(-1.850, -0.023)	-2.85	0.047	*		
P. Stage								
CL	0.421	0.329	(-0.493, 1.334)	1.28	0.270	1.33		
FT	-0.127	0.329	(-1.040, 0.786)	-0.39	0.719	1.33		

WB	-0.294	0.329	(-1.207, 0.620)	-0.89	0.422	*
Regression Equation						
Response time (min) = 1.460 + 1.873 LoA_4 - 0.937 LoA_5 - 0.937 LoA_6 + 0.421 P. Stage_CL - 0.127 P. Stage_FT - 0.294 P. Stage_WB						
Means						
Term	*Fitted Mean*	*SE Mean*				
LoA						
4	3.333	0.403				
5	0.524	0.403				
6	0.524	0.403				
P. Stage						
CL	1.881	0.403				
FT	1.333	0.403				
WB	1.167	0.403				

α = 0.05 significance level

In Table *4-2*, there are two factors included in the analysis, LoA and P.Stage. Both factors are fixed, the LoA factor has 3 levels with values 4, 5, and 6. The P.Stage factor has three levels with values CL, FT and WB.

The effects of LoA and the process stage were assessed. The commonly chosen α-level of 0.05 was chosen and the results indicate the following: The p-value for the LoA factor given as 0.012 is less than 0.05. Since this is less than the chosen α-level of 0.05, it means the effect of LoA on response time is significant. In other words, the mean response time is different for the different LoA while that of the P.Stage (0.489) is greater than 0.05, indicating that there is no significant effect of P.Stage on response time, implying that the mean response time is the same for a given LoA at different P.Stages. S is 0.697826, R is 89.51%, and adjusted R equals 79.02% which indicates that the model explains 89.51% of the variation in response time when you use it for prediction. This is good for comparing different response time models since S is minimal and R maximum. LoA is significant at all three levels (p= 0.005, 0.047, and 0.047) since they are all less than $\alpha = 0.05$ while the P.Stage is not significant at all three levels (p= 0.270, 0.719, 0.422). All p-values are greater than α-level of 0.05. Consequently, the effect of one predictor does not depend on the value of the other predictor. Also, The VIFs are all less than 5, which indicates that the predictors are not highly correlated.

From the regression equation in Table 4-2, the results of the mean response time analysis indicate that (LoA = 4) Conventional provides the highest average response time (3.333 min) while SCADA (LoA = 5) and DCS (LoA = 6) results to 0.523 min each.

For relationship analysis, let:

H_o: There is no linear relationship between LoA and response time to anomaly (All the population means for the various treatments are equal)

H_1: There exist a functional relationship between LoA and response time to anomaly. True if $F_{cal} > F_{crit}$.

Since F_{cal} (16.21) > F_{crit}, (6.94) for LoA, H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and response time. While for P.Stage F_{cal} (0.86) < F_{crit}, (6.94), thus H_o is not rejected and it is concluded that at 95% confidence level, there is no sufficient evidence that there exist a relationship between P.stage and response time.

Also, from the negatively sloped correlation curves in *Figure 4-2*, the response time is inversely proportional to the LoA.

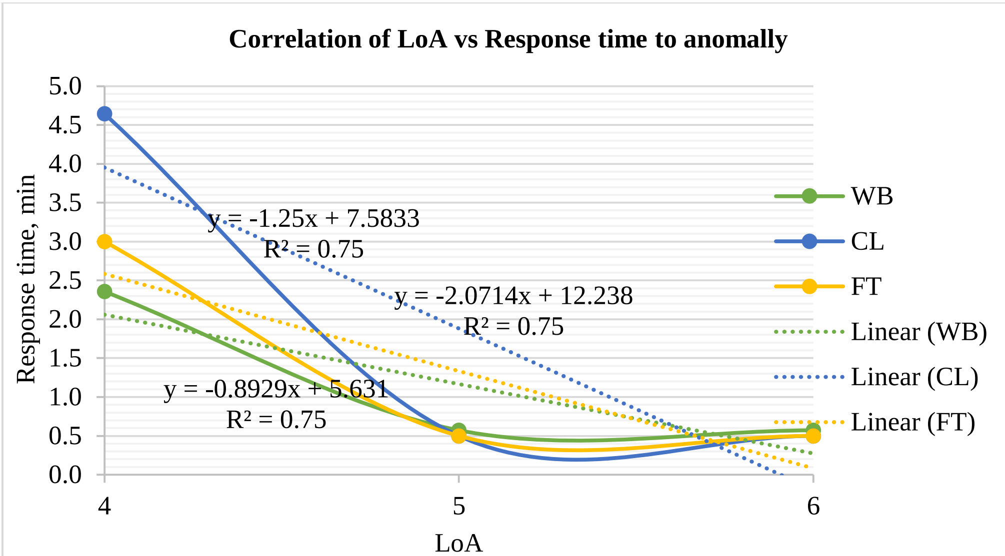

Figure 4-2 Correlation of LoA vs Response time (min) (Source: Field data, 2019)

The basic criterion of performance in a production system is response time. In ordinary production processes, the response time is measured in the range of five to ten millisecond. Thus, the response time in a process is reasonable if it is at its lowest value to demonstrate the rapid rate at which an anomaly can be detected by the system and appropriate action taken. Based on this, LoA 5 and 6 provides the best response time in the process line. Thus, either of the two LoA is viable to be adopted for real time monitoring of processes and subsequently adaptive control.

In a case of the computer processor, to check whether the performance of a CICS® system is in line with the system's required capability, then investigations should be on the hardware, the software, and the applications that are in the installation.

However, response time depends on the speed of the processor, and on the nature of the application being run on the production system. Thus the shorter the response time, the more rapid a process will be executed in a production system. Also to note, is the consistency of the response times. Sharp variations will imply erroneous system operation.

The sensitivity test for the response time on a range of 95% CI in Figure 4-3, depicts that the residuals appear to follow a straight line. There is no evidence of non-normality, skewness, outliers, or unidentified variables that exists.

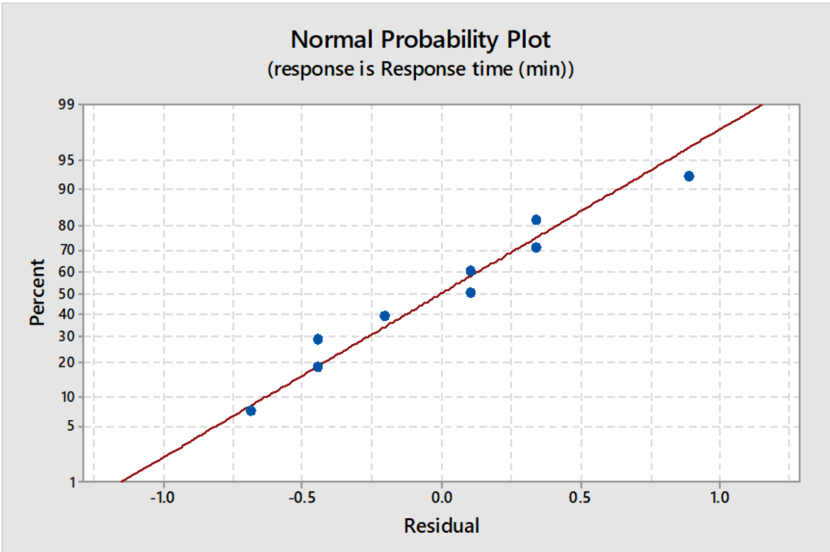

Figure 4-3 Normal probability plot for response time at 95% CI (Source: Field data, 2019)

4.2.2 Process temperature variability

For the experiment conducted, the process temperature variability for three different level of automation (LoA 4, LoA 5 and LoA 6) was taken in four process stages where it was applicable namely HD KNIV, SHREDD, KNV and EXTRACTN as shown in Table 4-3 and *Figure 4-4*.

Table 4-3 Summary of process temperature variability for different LoA (Source: Field data, 2019)

		Process temperature variability (ºC)							
Stage	**Level**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Avg**
HD KNIV	HD KNIV(LoA 4)	0	3	3	0	3	4	2	**2**
	HD KNIV(LoA 5)	0	0	0	0	0	0	0	**0**
	HD KNIV(LoA 6)	0	0	0	0	0	0	0	**0**
SHREDD	SHREDD(LoA 4)	0	3	5	0	4	4	2	**3**
	SHREDD(LoA 5)	0	0	0	0	0	0	0	**0**
	SHREDD(LoA 6)	0	0	0	0	0	0	0	**0**
KNIV	KNIV(LoA 4)	0	5	3	2	3	0	4	**2**
	KNIV(LoA 5)	0	0	0	0	0	0	0	**0**
	KNIV(LoA 6)	0	0	0	0	0	0	0	**0**
EXTRACTN	EXTRACT(LoA 4)	5	4	5	5	5	4	3	**4**
	EXTRACT(LoA 5)	0	0	0	0	0	0	0	**0**
	EXTRACT(LoA 6)	0	0	0	0	0	0	0	**0**

The process temperature were always to be maintained at 60° C for the chopping, shredding and high density knifing stages and 80° C for the extraction stage. Table *4-3* reveals that, using the conventional automation (LoA 4) at the chopping stage (HD KNIV), shredding and juice extraction resulted to an average temperature variability of 2°C, 3°C and 4°C respectively. While the SCADA (LoA 5) and DCS (LoA 6) showed no temperature variability in the three process stages. The lowest temperature variability in the conventional automation was 1°C recorded at HD KNIV (replicate 1) and the highest temperature variability being 5 °C at SHREDD (replicates 3) and EXTRACTN (replicate 1, 3, 4, and 5).

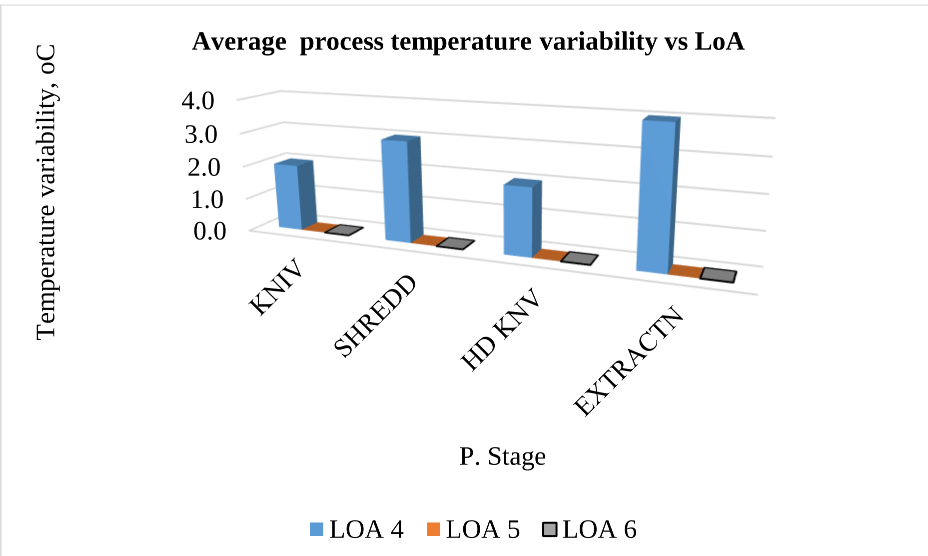

Figure 4-4 Average temperature variability for different LoA (Source: Field data, 2019)

From Figure 4-4, it is evident that LoA 4 has the highest mean temperature variability in all the four process stages while both LoA 5 and LoA 6 indicated the lowest mean temperature variability. The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on process temperature variability. There were 7 replicates for each separate treatment levels under investigation.

Table 4-4 ANOVA for Process temp variability (^{0}C) versus LoA, P. Stage (Source: Field data, 2019)

Factor Information

Factor	*Type*	*Levels*	*Values*
LoA	Fixed	3	4, 5, 6
P. Stage	Fixed	4	EXTRACTN, HD KNV, KNIV, SHREDD

Analysis of Variance

Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*F-Crit*
LoA	2	20.1667	88.00%	20.1667	10.0833	33.00	0.001	5.14
P. Stage	3	0.9167	4.00%	0.9167	0.3056	1.00	0.455	4.75
Error	6	1.8333	8.00%	1.8333	0.3056			
Total	11	22.9167	100.00%					

Model Summary

S	*R-sq*	*R-sq(adj)*	*PRESS*	*R-sq(pred)*
0.552771	92.00%	85.33%	7.33333	68.00%

Coefficients

Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*
Constant	0.917	0.160	(0.526, 1.307)	5.74	0.001	
LoA						
4	1.833	0.226	(1.281, 2.386)	8.12	0.000	1.33
5	-0.917	0.226	(-1.469, -0.364)	-4.06	0.007	1.33
6	-0.917	0.226	(-1.469, -0.364)	-4.06	0.007	*
P. Stage						
EXTRACTN	0.417	0.276	(-0.260, 1.093)	1.51	0.182	1.50
HD KNV	-0.250	0.276	(-0.926, 0.426)	-0.90	0.401	1.50
KNIV	-0.250	0.276	(-0.926, 0.426)	-0.90	0.401	1.50
SHREDD	0.083	0.276	(-0.593, 0.760)	0.30	0.773	*

Regression Equation

Process temp Var (0C) = 0.917 + 1.833 LoA_4 - 0.917 LoA_5 - 0.917 LoA_6
+ 0.417 P. Stage_EXTRACTN - 0.250 P. Stage_HD KNV - 0.250 P. Stage_KNIV
+ 0.083 P. Stage_SHREDD

Means

Term	*Fitted Mean*	*SE Mean*
LoA		
4	2.750	0.276
5	-0.000	0.276
6	-0.000	0.276
P. Stage		
EXTRACTN	1.333	0.319
HD KNV	0.667	0.319
KNIV	0.667	0.319
SHREDD	1.000	0.319

α = 0.05 significance level

From Table *4-4*, there are two factors included in the analysis, LoA and P.Stage. Both factors are fixed, the LoA factor has 3 levels with values 4, 5, and 6. The P.Stage factor has four levels with values EXTRACTN, HD KNV, KNIV, and SHREDD.

From the ANOVA, the effects of LoA and the process stage were assessed. The significance level of 0.05 was chosen and the results indicated that, the p-value for the LoA factor given as 0.001 is less than 0.05. Since this is less than the chosen α-level of 0.05, it means the effect of LoA on response time is significant. In other words, the mean process temperature variability is different for the different LoA while that of the P.Stage (0.455) is greater than 0.05, indicating that there is no significant effect of P.Stage on process temperature, implying that the mean process temperature variability is the same for a given LoA at different P.Stages. S is 0.5527, R is 92%, and adjusted R equals 85.33% which indicates that the model explains 92% of the variation in process temperature variability when you use it for prediction. This is good for comparing different process temperature models since S is minimal and R maximum.

From the coefficient, LoA is significant at all three levels (p = 0.000, 0.007, and 0.007) since they are all less than α = 0.05 while the P.Stage is not significant at all four levels (p= 0.182, 0.401, 0.40, 0.773) since all p-values are greater than the α-level of 0.05. This implies that the effect of one predictor does not depend on the value of the other predictor. Also, the VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equation, employing Conventional automation (LoA = 4) in the 4 process stages applicable, the mean variability in process temperature is (0.917 + 0.417 - 0.250 - 0.250 + 0.083 + 1.833)2.75^{o} C, while SCADA (LoA = 5) and DCS (LoA = 6) results to no temperature variability (0^{o} C) in each.

The results of the mean temperature changes indicate that (LoA = 4) Conventional automation provides the highest average temperature variability (2.75^o C) while SCADA (LoA = 5) and DCS (LoA = 6) results to 0^o C each.

For relationship analysis, let:

> H_o: There is no linear relationship between LoA and temperature variability (All the population means for the various treatments are equal)
>
> H_1: There exist a functional relationship between LoA and temperature variability. True if $F_{cal} > F_{crit}$.

Since for LoA, F_{cal} (33.0) > F_{crit}, (5.14), H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and process temperature variability. While for P.Stage F_{cal} (1.00) < F_{crit}, (4.75), thus H_o is not rejected and it is concluded that at 95% confidence level, there is no sufficient evidence that there exist a relationship between P.stage and temperature variability.

Also, from the negatively sloped correlation curves with high Pearson's coefficient 0.75 in *Figure 4-5*, the variability in process temperature is inversely proportional to the LoA.

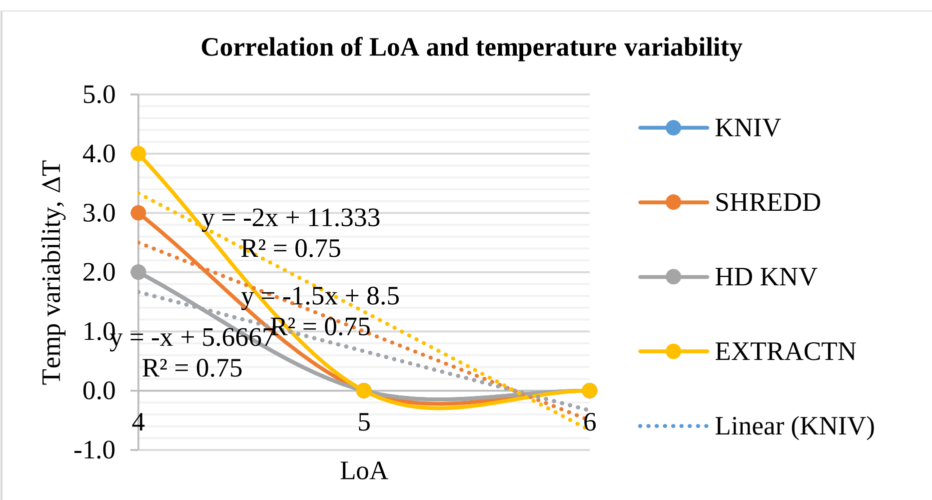

Figure 4-5: Correlation of process temperature variability vs LoA (Source: Field data, 2019)

According to Panpae et.al (2008), the rate of sucrose inversion in sugar cane juice extraction is largely depended on the solid content, temperature and pH. When these parameters are increased, they equally increase sucrose inversion rate. To lower the total reducing sugar, temperature control is important in regulating the sucrose inversion while a high pH in the OH^- from lime slightly affects the properties of the juice extract in comparison to the high apparent purity of the pure sugarcane juice. It was observed that at 80°C, sugars and %pol magnitudes were relatively significant compared to lower temperatures. However, when solid content was increased at 80°C, it recorded a lower %pol which is the sucrose content. Therefore, juice extraction process is highly depended on the pH and temperature fluctuations, which must then be maintained for optimum production.

From *Figure 4-6*, the sensitivity test for the process temperature variability on a range of 10% to 95% CI depicts that the residuals appear to follow a straight line. There is no evidence of non-normality, skewness, outliers, or unidentified variables that exists.

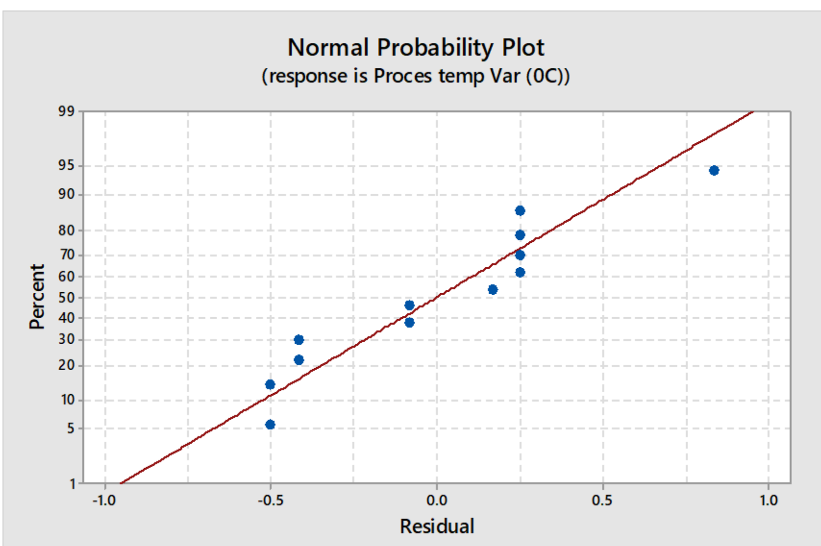

Figure 4-6 Normal probability plot for process temperature variability (Source: Field data, 2019)

4.2.3 Process pH variability

For the experiment conducted, the process temperature variability for three different level of automation (LoA 4, LoA 5 and LoA 6) was taken in a single process stages where it was applicable namely EXTRACTN as shown in Figure *4-7*.

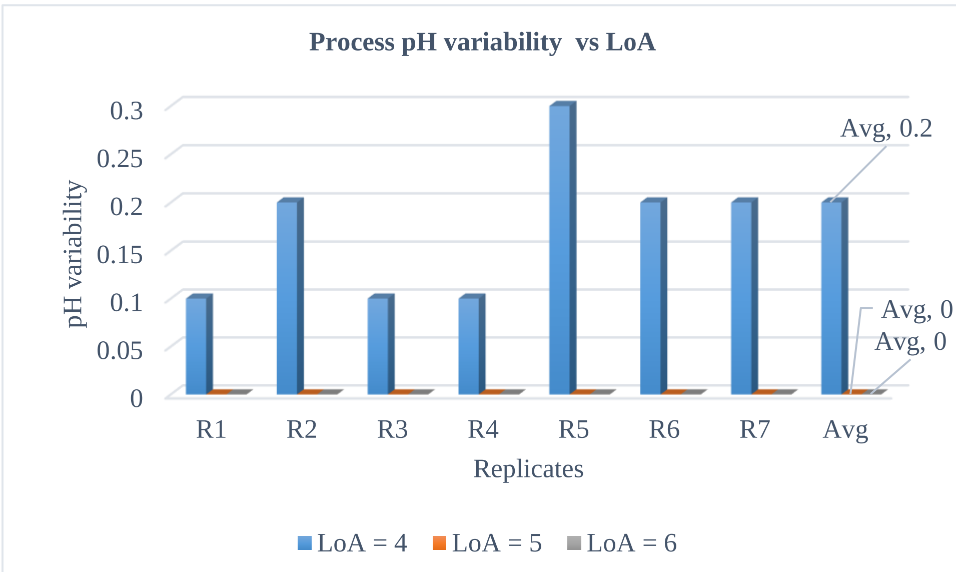

Figure 4-7 Process pH variability graph (Source: Researcher, 2019)

The process pH was always to be maintained at 6.5 for the extraction stage. Figure *4-7* reveals that, using the conventional automation (LoA 4) resulted to an average pH variability of 0.2, while the SCADA (LoA 5) and DCS (LoA 6) showed no pH variability. The lowest pH variability in the conventional automation was 0.1 while the highest being 0.3. It is observed that LoA 4 has the highest mean temperature variability at the extraction process stages while both LoA 5 and LoA 6 indicated the lowest mean temperature variability of 0.

The experiment was a randomized block being investigated on pH variability. There were 7 replicates for each separate treatment levels under investigation.

Table 4-5 ANOVA for Process pH variability versus LoA, P. Stage (Source: Field data, 2019)

Factor Information							
Factor	*Type*	*Levels*	*Values*				
LoA	Fixed	3	4, 5, 6				
Analysis of Variance							
Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*
LoA	2	0.02667	100.00%	0.02667	0.01333	0.0001	0.0001
Error	0	0.0001	0.0001	0.0001	0.0001		
Total	2	0.02667	100.00%				
Model Summary							
S	*R-sq*	*R-sq(adj)*	*PRESS*	*R-sq(pred)*			
*	100.0%	0.0001	0.0001	0.0001			
Coefficients							
Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*	
Constant	0.06667	0.0001	(0.0001, 0.0001)	0.0001	0.0001		
LoA							
4	0.1333	0.0001	(0.0001, 0.0001)	0.0001	0.0001	1.33	
5	-0.06667	0.0001	(0.0001, 0.0001)	0.0001	0.0001	1.33	
6	-0.06667	0.0001	(0.0001, 0.0001)	0.0001	0.0001	0.0001	
Regression Equation							
Process pH = 0.06667 + 0.1333 LoA_4 - 0.06667 LoA_5 - 0.06667 LoA_6							
Means							
Term	*Fitted Mean*	*SE Mean*					
LoA							
4	0.2000	0.0001					
5	-0.000000	0.0001					
6	0.000000	0.0001					

* = infinitesimally small; α = 0.05 Significance level

From Table *4-5*, there is one factor under analysis which is LoA with 3 levels of values 4, 5, and 6. In the ANOVA table, the effects of LoA was assessed. The significance level of 0.05 was chosen and the results indicated that, the p-value for the LoA factor given as * is infinitesimally smaller than 0.05. Since this is less than the chosen α-level of 0.05, it means the effect of LoA on pH variation is significant. In other words, the mean pH variability is different for the different LoA. R is 100%, which indicates that the model explains 100% of the variations in pH when you use it for prediction. This is good for comparing different pH models since R is maximum.

From the coefficient, LoA is significant at all three levels (p = ***)** since they are all less than $\alpha = 0.05$. This implies that the effect of one predictor does not depend on the value of the other predictor. Also, the VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equation, employing Conventional automation (LoA = 4) at the extraction stage, the mean variability in pH is (0.06667 + 0.1333) 0.2, while SCADA (LoA = 5) and DCS (LoA = 6) results to no pH (0) in each. The results of the mean pH changes indicate that (LoA = 4) Conventional automation provides the highest average pH variability (0.2) while SCADA (LoA = 5) and DCS (LoA = 6) results to 0 each. This can be attributed to the precision offered by SCADA and DCS in monitoring any changes.

4.2.4 Adaptive control

The experiment was a randomized block with two factors (LoA and P.Stage) investigated on three key indicators that affect adaptive control through real time monitoring namely response time, process temperature variability and pH variability. There were 7 replicates for each separate treatment levels under investigation. From Eq. 3-12, the adaptive control index was evaluated and recorded as shown in Table *4-6* and Figure *4-8*

Table 4-6: Adaptive control parameter indices vs LoA

Average Parameters for Adaptive control	**Conventional automation (LoA 4)**	**SCADA (LoA 5)**	**DCS (LoA 6)**
Response time (min), y_{11}	3.3	0.5	0.5
Process temp variabilty (ºC), y_{12}	2.8	0.0	0.0
Process pH variability, y_{13}	0.2	0.0	0.0
Adaptive control index, y_1	**2.5**	**0.2**	**0.2**

$$Adaptive\ control\ index\ (y_1) = \frac{2}{5}\left(\frac{\sum_1^3 y_{11}}{3}\right) + \frac{2}{5}\left(\frac{\sum_1^4 y_{12}}{4}\right) + \frac{1}{5} y_{13}$$

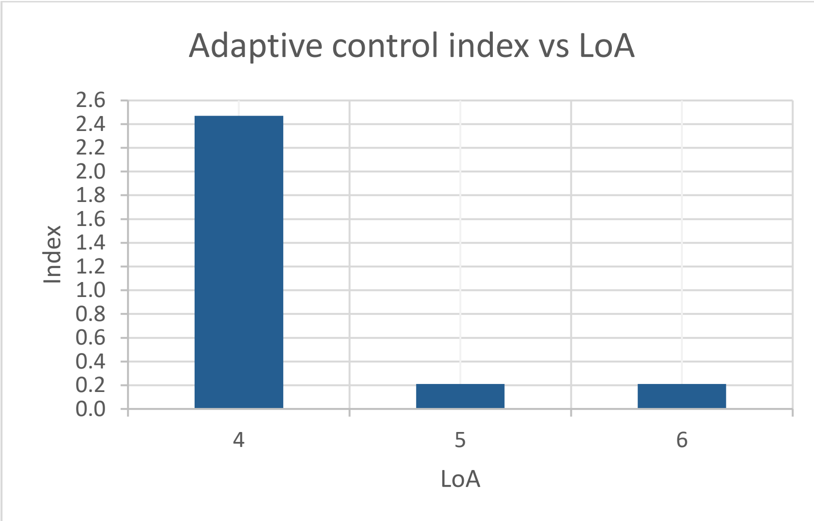

Figure 4-8: Adaptive control index vs LoA

The results in Table *4-6* indicated that the means of 3 adaptive control parameters decreased when the LoA increased. Furthermore, Figure *4-8* revealed that adaptive control index reduced from LoA 4 through LoA 5 to LoA 6, suggesting that either LoA 5 or 6 is the optimum for attaining real time monitoring of process due to their negligible variability in process parameters. This concurs with Martinez et.al, 2001 who alluded that for optimum real time monitoring, the responsible manufacturing indicators must decrease.

Since $\mu_{\,LoA\,4} \neq \mu_{\,LoA\,5} \neq \mu_{\,LoA\,6}$ it can be asserted that there is a relationship between LoA and adaptive process control.

The analysis is summarized in both the probability plot and summarized ANOVA table shown below.

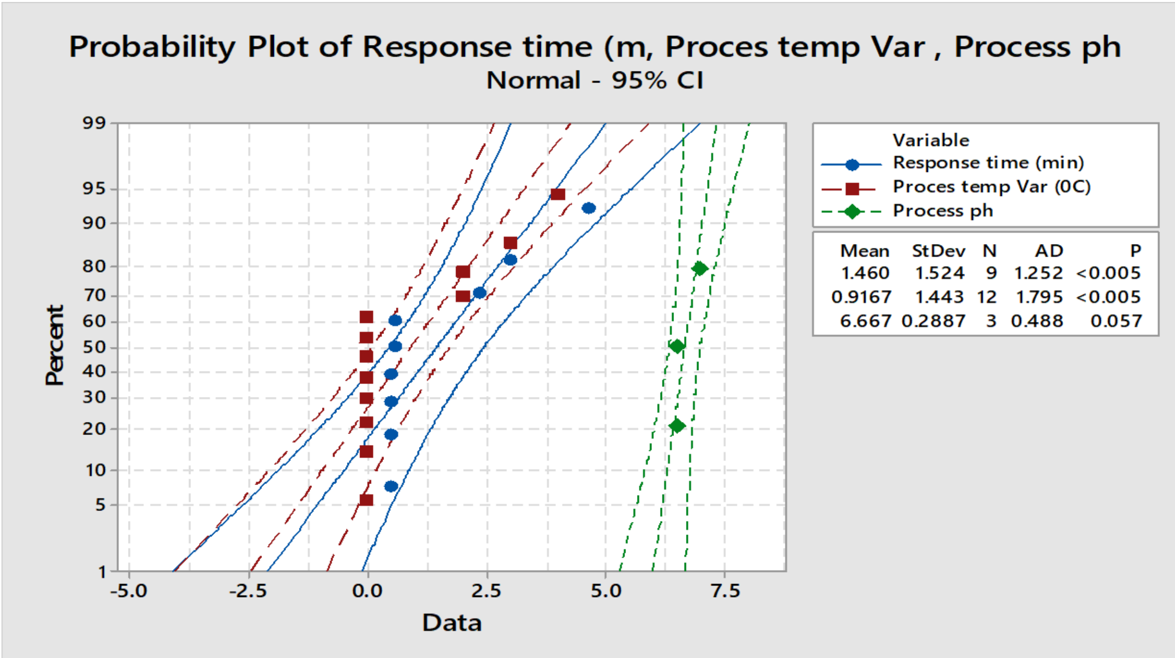

Figure 4-9 Probability plot of Response time, Process temperature variability and Process pH for 5 - 95% CI (Source, Field data, 2019)

Table 4-7 Analysis for impact of lean automation on adaptive process control (Source: Field data, 2019)

Description	**LoA**	**No. of P.stages**	**Mean**	**Variance**	**Test for significance (ANOVA)**
Response time to anomaly	LoA 4 LoA 5 LoA 6	3 3 3	3.33 0.54 0.54	1.3894 0.0017 0.0017	F_{Calc} = 16.21 F_{Crit} = 6.94 P-Value = 0.012 α = 0.05 DF = 2 $F_{Calc} > F_{Crit}$ and α > P-Value Com = Significant at 0.05 level
Process temperature variability	LoA 4 LoA 5 LoA 6	4 4 4	2.75 0 0	0.9167 0 0	F_{Calc} = 33.00 F_{Crit} = 5.14 P-Value = 0.001 α = 0.05 DF = 3 $F_{Calc} > F_{Crit}$ and α > P-Value Com = Significant at 0.05 level
pH variability	LoA 4 LoA 5 LoA 6	1 1 1	0.2 0 0	0	F_{Calc} = 65535 F_{Crit} = 0 P-Value = 0 α = 0.05 DF = 0 $F_{Calc} > F_{Crit}$ and α > P-Value Com = Significant at 0.05 level

From both Figure *4-9* and Table *4-7*, adaptive control in the sugar processing was evaluated by three variables namely: response time, process temperature variability and the process pH control. The response time to an anomaly conducted in three stages showed that level 4 of automation had a slow response to anomaly with the longest mean response time of 2.4-4.6 minutes compared to levels 5 and 6 which depicted a rapid response to anomaly with the shortest response time of 0.5 min. Also, conventional automation (LoA 4) at the chopping stage (HD KNIV), shredding and juice extraction resulted to an average temperature variability of 2^oC, 3^oC and 4^oC respectively. While the SCADA (LoA 5) and DCS (LoA 6) showed no temperature variability in the three process stages. The lowest temperature variability in the conventional automation was 1^oC recorded at HD KNIV (replicate 1) and the highest temperature variability being 5^oC at SHREDD (replicates 3) and EXTRACTN (replicate 1, 3, 4, and 5). It is evident that LoA 4 has the highest temperature variability in the three process stages while both LoA 5 and 6 indicated the lowest temperature variability. Unlike in levels 5 and 6 where set temperatures are easily monitored, controlled and maintained by the system. This applies to pH control too. Thus, adopting levels 5 or 6 the process parameters are controlled and maintained at the optimum levels. This is in line with the requirement that the optimum process temperatures at the Knives, shredders and heavy duty knives should be maintained at 60^oC, while at the extraction stage 85^oC should be maintained to enhance dissociation of sugars from the fibers. Also, a mild acidic condition of pH 6.5 should be maintained to prevent the survival of bacteria and microorganisms

From the analysis of variance, the p-values for LoA and stage respectively $< \alpha = 0.05$, it is concluded that there is a statistically significant association between the response variables and the term. The modal explains 89.51% of the variation in the response. S indicates that the standard deviation between the data points and the fitted values is approximately 0.698 units.

From the coefficients table, all the variance inflation factor (VIF) are in the range of 1 to 5 thus the parameters are moderately correlated, thus no much multicollinearity in the variances.

Furthermore, the model equation for the response time, process temperature monitoring and pH variability depicts increasing values in level 4 due to (+) sign and reducing values both in levels 5 and 6 due to (-) sign. This implies that LoA 5 or 6 is the optimum automation level for real time monitoring in a sugar industry if adaptive control is to be achieved. From the probability plot in Figure 4-9, all the three parameters have $p < 0.05$. Therefore, results are significant.

This conforms to the findings of Gambier (2004) who asserted that, the correctness of an output in a real-time monitoring system does not only depend on the logical accuracy of the calculation but also on the time at which the output is displayed. According to Gambier (2004), this assertion validates the importance of time factor for a real time setup in any manufacturing and industrial system, and that there exist timing constraints which will always hinder cycle times of manufacturing tasks. As a result, these tasks must be able to synchronize with the real-time events in the external environment within the industry. Therefore, a real-time setup must synchronize with the external events associated with it.

According to Panpae et.al (2008), the rate of sucrose inversion in sugar cane juice extraction is largely depended on the solid content, temperature and pH. When these parameters are increased, they equally increase sucrose inversion rate. To lower the total reducing sugar, temperature control is important in regulating the sucrose inversion while a high pH in the OH^- from lime slightly affects the properties of the juice extract in comparison to the high apparent purity of the pure sugarcane juice. It was observed that at 80°C, the extent of sugars and %pol magnitudes were relatively significant compared to lower temperatures. However, when solid content was increased at 80°C, it recorded a lower %pol which is the sucrose content. Therefore, juice extraction process is highly depended on the pH and temperature fluctuations, which must then be maintained for optimum production. This critical contribution of pH, temperature and response time regulation serves a good reason for all the local sugar industries to adopt LoA 5 (SCADA) or 6 (DCS) for its processes.

In addition, it concurs with Six Sigma theory, which emphasizes on reduction of variations to enhance processes. Through the help of statistical techniques, it is possible to forecast the process outcomes. If unexpected outcome is noticed, then advanced control tools can be used to explain the phenomenon. In relation to lean automation, the integration of lean and proper levels of automation provides a suitable advanced control tool to best understand and identify parameters that affect or vary the process, and hence the overall performance of the organization (Dave, 2002)

Therefore, levels 5 or 6 of automation will provide a steadfast real time monitoring, control and maintenance of process parameters that will enhance quality production.

4.3 Potential of lean automation on improving production quality.

A high rate of production in manufacturing processes is attributed to many indicators, among them, higher productivity with minimum defects in processes and products, which is possible only with higher rates of quality. For a competitive advantage, productivity and quality are very vital indicators for an industry to think of attaining its goals. High rate of productivity is rather the main content for improving quality and reducing defects, increasing profitability and decreasing costs. Manufacturing organizations that continuously produce high-quality products and are most productive have lower costs, higher profit margins, and monopolize a larger and larger share of the market. The guidance from recognized productivity and quality leaders provides a general framework for making improvement in quality efforts successful.

From Fig 2-1, it is noted that the effectiveness of an automated lean manufacturing to provide quality sugar production is subject to the extent with which the fibers are scattered to expose sucrose and the ability to extract the most sucrose concentration from the fibers. This is indicated by the PI and %brix respectively, which ultimately determines the apparent purity of the juice extract. The higher the PI and brix, the higher the apparent purity and consequently the quality of the sugar produced within the manufacturing line and vice versa.

In this experiment, production quality was demonstrated by three major parameters namely brix, pol and Preparation Index (PI) which were measured at the respective stages of the sugar pre-process line for different levels of automation. The purity of sugar juice when using different levels of automation was calculated from the values of brix and pol measured and then analyzed to ascertain the level of automation that will give the best sugar purity.

4.3.1 Preparation index (PI)

For the experiment conducted, PI for three different level of automation (LoA 4, LoA 5 and LoA 6) was determined in three process stages where it was applicable namely KNIV, SHREDD and HD KNV.

Table 4-8: PI for different LoA (Source: Field data, 2019)

		%PI for different replicates							
Stage	Level	R1	R2	R3	R4	R5	R6	R7	**AVG**
KNIV	KNIV(LoA 4)	64	65	64	65	67	65	64	**65**
	KNIV(LoA 5)	68	69	68	69	69	68	69	**69**
	KNIV(LoA 6)	70	68	69	70	70	70	70	**70**
SHREDD	SHREDD(LoA 4)	76	77	76	79	78	76	75	**77**
	SHREDD(LoA 5)	80	81	82	81	80	81	81	**81**
	SHREDD(LoA 6)	85	84	85	84	84	86	84	**85**
HD KNIV	HD KNIV(LoA 4)	-	-	-	-	-	-	-	**-**
	HD KNIV(LoA 5)	92	93	92	92	91	90	92	**92**
	HD KNIV(LoA 6)	93	94	94	94	93	93	94	**94**

Table *4-8* reveals that the three stages namely KNIV, SHREDD and HD KNIV are cascaded and the PI increases sequentially along the cascade from the KNIV to HD KNIV. Similarly, in all the stages, conventional automation (LoA 4) recorded the least PI value with an average of 65% and 77% at the KNIV and SHREDD stages respectively. The HD KNIV is not applicable with the 4^{th} LoA but was estimated at a value of 89%. However, with SCADA mostly used with diffuser the PI values were relatively high with an average of 69%, 81% and 92% for KNIV, SHREDD and HD KNV respectively. While DCS recorded the highest PI values of 70%, 85% and 94% at KNIV, SHREDD and HD KNV stages respectively. The PI values increases along the cascade from KNIV to HD KNIV because of the nature and type of chopping mechanism with the KNIV having sharp cutting knives while HD KNIV possessing smooth discs hence KNIV producing rough and coarse chips of low PI wile HD KNIV producing very fine chips of high PI.

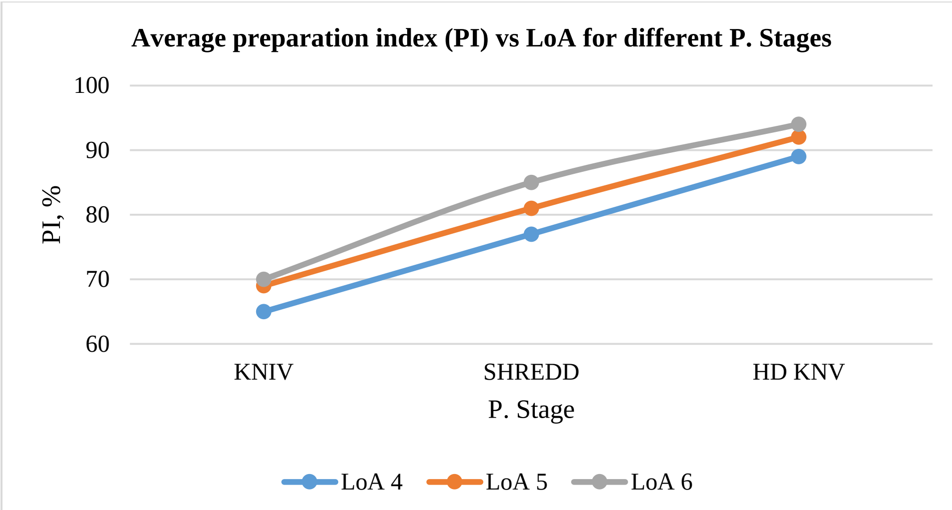

Figure 4-10 PI graph for different LoA and P.Stage (Source: Field data, 2019)

From Figure 4-10, LoA 4 has the lowest mean PI of 65%, 77% and 89 at the KNIV, SHREDD and HD KNV respectively, as opposed to both LoA 5 and 6 that recorded relatively high mean PI. It is therefore evident that, the higher the level of automation the higher the %PI.

The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on PI. There were 7 replicates for each separate treatment levels under investigation.

Table 4-9 ANOVA for PI (%) versus LoA and P. Stage

Factor Information								
Factor	*Type*	*Levels*	*Values*					
LoA	Fixed	3	4, 5, 6					
P. Stage	Fixed	3	HD KNV, KNIV, SHREDD					
Analysis of Variance								
Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*F-Crit*
LoA	2	54.889	6.09%	54.889	27.444	29.06	0.004	6.94
P. Stage	2	842.889	93.49%	842.889	421.444	446.24	0.000	6.94
Error	4	3.778	0.42%	3.778	0.944			
Total	8	901.556	100.00%					
Model Summary								
S	*R-sq*	*R-sq(adj)*	*PRESS*	*R-sq(pred)*				
0.971825	99.58%	99.16%	19.125	97.88%				

Coefficients						
Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*
Constant	80.222	0.324	(79.323, 81.122)	247.64	0.000	
LoA						
4	-3.222	0.458	(-4.494, -1.950)	-7.03	0.002	1.33
5	0.444	0.458	(-0.828, 1.716)	0.97	0.387	1.33
6	2.778	0.458	(1.506, 4.050)	6.06	0.004	*
P. Stage						
HD KNV	11.444	0.458	(10.172, 12.716)	24.98	0.000	1.33
KNIV	-12.222	0.458	(-13.494, -10.950)	-26.68	0.000	1.33
SHREDD	0.778	0.458	(-0.494, 2.050)	1.70	0.165	*
Regression Equation						
PI(%) = 80.222 - 3.222 LoA_4 + 0.444 LoA_5 + 2.778 LoA_6 + 11.444 P. Stage_HD KNV - 12.222 P. Stage_KNIV + 0.778 P. Stage_SHREDD						
Means						
Term	Fitted Mean	SE Mean				
LoA						
4	77.000	0.561				
5	80.667	0.561				
6	83.000	0.561				
P. Stage						
HD KNV	91.667	0.561				
KNIV	68.000	0.561				
SHREDD	81.000	0.561				

α = 0.05 significance level

From Table 4-9, there are two factors included in the analysis, LoA and P.Stage. Both factors are fixed, the LoA factor has 3 levels with values 4, 5, and 6. The P.Stage factor has three levels with values HD KNV, KNIV and SHREDD.

In the analysis of variance, the effects of LoA and the process stage were assessed. The commonly chosen α-level of 0.05 was chosen and the results indicate the following: The p-value for the LoA factor given as 0.004 is less than 0.05. Since this is less than the chosen α-level of 0.05, it means the effect of LoA on PI is significant. In other words, the mean PI is different for the different LoA. Similarly, the p-value of the P.Stage (0.000) is less than 0.05, indicating that there is significant effect of P.Stage on PI, implying that the mean PI is different for a given LoA at different P.Stages. S is 0.971825, R is 99.58%, and adjusted R equals 99.16% which indicates that the model explains 99.58% of the variation in PI when you use it for prediction. This is good for comparing different PI models since R is maximum.

From ANOVA, The LoA is significant only at LoA 4 and 6 ($p = 0.002$ and 0.004) since they are all less than $\alpha=0.05$. LoA 5 has a p-value of 0.387 which is higher than 0.05, hence not significant in in explaining the relationship between LoA and PI. This is because LoA 5 almost similar to LoA 6. The P.Stage is also significant at the KNIV and HD KNIV with $p= 0.000$. This is less than 0.005. However, the SHREDD stage has a p-value of 0.165 hence not significant since it doesn’t apply to LoA 5. Consequently, the effect of one predictor does not depend on the value of the other predictor. Also, The VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equation, employing Conventional (LoA = 4) in the 3 process stages applicable gives a PI of (80.222 - 3.222 LoA_4 + 11.444 - 12.222 + 0.778) 77%, while SCADA (LoA = 5) gives a mean of 80.67% and DCS (LoA = 6) results to 83%. The relatively high PI by LoA 5 and 6 proves that either SCADA or DCS can be the best options for the sugar industry in attaining the optimum preparation index PI that exposes more of the sugar concentrate and thus improving the quality of sugar production.

For relationship analysis, let:

> H_o: There is no linear relationship between LoA and PI (All the population means for the various treatments are equal)
>
> H_1: There exist a functional relationship between LoA and PI. True if $F_{cal} > F_{crit}$.

Since for LoA, F_{cal} (29.06) > F_{crit}, (6.94), H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and PI. Similarly for P. Stage, F_{cal} (446.24) > F_{crit}, (6.94), thus H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between P.stage and PI.

Also, from the positively sloped correlation curves with high Pearson's coefficient of about 1 in Figure *4-11*, the variability in process temperature is directly proportional to the LoA.

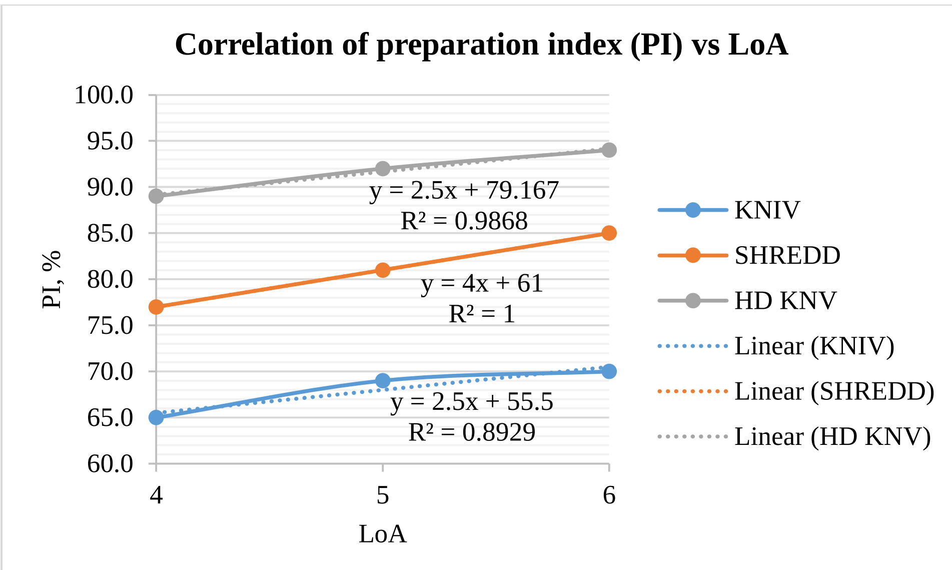

Figure 4-11 Coefficient graph of PI vs LoA for different P.stages (Source: Field data, 2019)

LoA 4 uses the open cell method which takes a shorter period to split the cane fibres using a single drum of knives since it is mostly installed with the mill tandems. However, this gives a low preparation index which does not promote a high extraction efficiency. Comparing this to LoA 5 or 6 where a diffuser is employed, the preparation-index method is employed. This requires an additional set of mechanisms to further split the fibres. Therefore the need of a shredder and high density knives. It may be thought of an additional power consumption to the plant, but if low power and variable speed controlled electro mechanical shredders and high density knives are chosen, the advantages of high preparation index and high extraction of juice will be attained.

This is in line with Kent and Lewinski (2007) who observed that for efficient cane preparation, the preparation index method provides higher result than the pol in open cells method. Also, advanced In-line shredders can easily replace even when processing whole-stick cane. Overall power consumption is less with a single shredder than with two sets of knives and a shredder as it is in the case of conventional automation.

From Figure 4-12, the sensitivity test for PI at 95% CI depicts that the residuals appear to follow a straight line. There is no evidence of non-normality, skewness, outliers, or unidentified variables that exists.

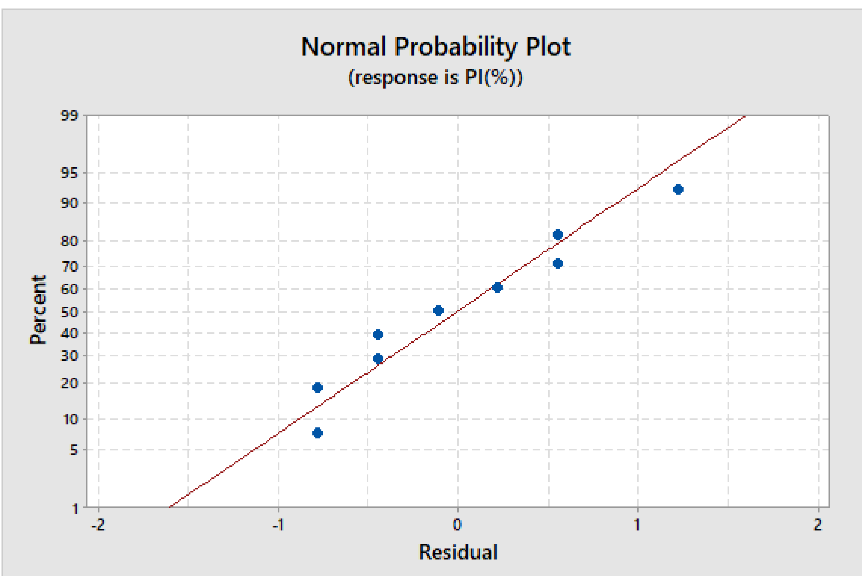

Figure 4-12 Normal probability plot for %PI (Source: Field data, 2019)

4.3.2 %Brix

The brix was measured in the laboratory using refractometer for the samples of juices collected at the relevant process stages. The juice samples from the four process stages were measured when different levels of automation were employed. For the experiment conducted, %brix for three different levels of automation (LoA 4, LoA 5 and LoA 6) was determined in four process stages where it was applicable namely KNIV, SHREDD, HD KNV and EXTRACT as shown in Table *4-10* and Figure 4-13.

Table 4-10 Summary of %Brix for different LoA (Source: Field data, 2019)

	Replicates (%)							
Level	R1	R2	R3	R4	R5	R6	R7	AVG
KNIV(LoA 4)	12.5	12.5	12.5	12	12.5	13	12.5	12.5
KNIV(LoA 5)	13	13.7	13.6	13.8	13.6	13.6	13.6	13.6
KNIV(LoA 6)	13	13.7	13.6	13.8	13.6	13.6	13.6	13.6
SHREDD(LoA 4)	13	13	13.1	13.1	13	13	13	13.0
SHREDD(LoA 5)	15.5	14.9	15	15	14.5	15	15	15.0
SHREDD(LoA 6)	15	15.2	14.8	14.8	15	15	15	15.0
HD KNIV(LoA 4)	-	-	-	-	-	-	-	-
HD KNIV(LoA 5)	16	16	15.9	16	16	15.9	16	16.0
HD KNIV(LoA 6)	16.2	15.8	16	15.9	16	16.1	16	16.0
EXTRACT(LoA 4)	17	16.9	17.2	17	16.9	17	17	17.0
EXTRACT(LoA 5)	18	17.9	17.8	18.1	18.1	18	18	18.0
EXTRACT(LoA 6)	17.8	18.2	17.9	18.2	18.1	18.2	17.9	18.0

Table *4-10* reveals that in all the stages, conventional automation (LoA 4) recorded the least %brix value with an average of 12.5%, 13% and 17% at the KNIV, SHREDD and SHREDD stages respectively. The HD KNIV was not applicable with the 4th LoA but was estimated at a value of 15 %. However, with SCADA and DCS mostly used with diffuser the % brix values were relatively high with an average of 13.6%, 15.0%, 16% and 18% for KNIV, SHREDD and HD KNIV and EXTRACT respectively. The three stages namely KNIV, SHREDD and HD KNIV and EXTRACTN are cascaded and the %brix increases sequentially along the cascade from the KNIV to EXTRACTN. This can be attributed to the nature and type of chopping mechanism with the KNIV having sharp cutting knives while HD KNIV possessing smooth discs hence KNIV producing rough and coarse chips of low %brix wile HD KNIV producing very fine chips of high %brix.

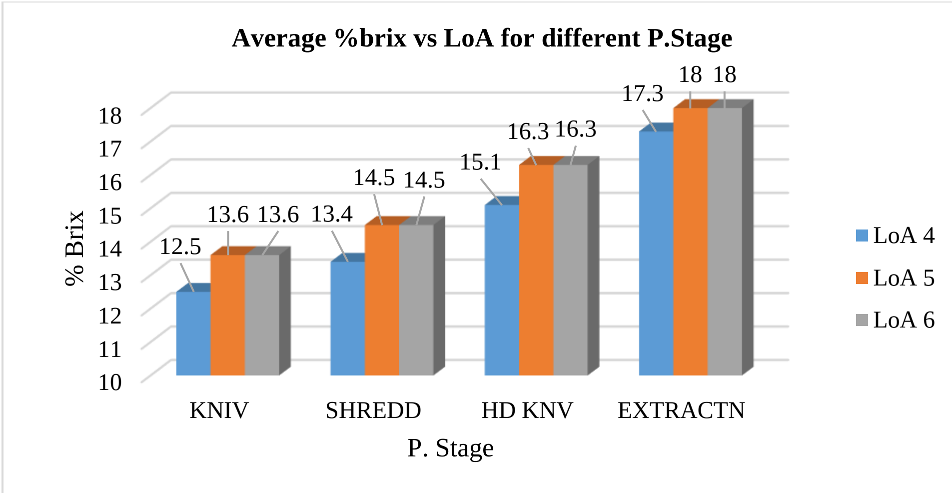

Figure 4-13 Graph of the average % Brix of the sugar juice for different LoA employed (Source: Field data, 2019)

From Figure 4-13. The convectional mill tandems (LoA 4) recorded the least overall % brix averagely 16.9%, while SCADA (LoA 5) and DCS (LoA 6) recorded averagely 18% each. Since brix % is a measure of the sucrose concentration, it shows that higher sucrose concentrations can be extracted from the sugar cane if a diffuser and the adoption of SCADA or DCS are employed.

The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on % brix. There were 7 replicates for each separate treatment levels under investigation.

Table 4-11 ANOVA for % Brix in juice versus LoA and P. Stage

Factor Information

Factor	*Type*	*Levels*	*Values*
LoA	Fixed	3	4, 5, 6
P. Stage	Fixed	4	EXTRACTN, HD KNV, KNIV, SHREDD

Analysis of Variance

Source	*DF*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*F-Crit*
LoA	2	2.8017	1.4008	85.47	0.000	5.14
P. Stage	3	36.2092	12.0697	736.46	0.000	4.76
Error	6	0.0983	0.0164			
Total	11	39.1092				

Model Summary

S	*R-sq*	*R-sq(adj)*	*R-sq(pred)*
0.128019	99.75%	99.54%	98.99%

Coefficients

Term	*Coef*	*SE Coef*	*T-Value*	*P-Value*	*VIF*
Constant	15.2583	0.0370	412.88	0.000	
LoA					
4	-0.6833	0.0523	-13.07	0.000	1.33
5	0.3417	0.0523	6.54	0.001	1.33
6	0.3417	0.0523	6.54	0.001	*
P. Stage					
EXTRACTN	2.5083	0.0640	39.19	0.000	1.50
HD KNV	0.6417	0.0640	10.02	0.000	1.50
KNIV	-2.0250	0.0640	-31.64	0.000	1.50
SHREDD	-1.1250	0.0640	-17.58	0.000	*

Regression Equation

Brix in juice (%) = 15.2583 - 0.6833 LoA_4 + 0.3417 LoA_5 + 0.3417 LoA_6+ 2.5083 P. Stage_EXTRACTN + 0.6417 P. Stage_HD KNV- 2.0250 P. Stage_KNIV - 1.1250 P. Stage_SHREDD

Means

Term	*Fitted Mean*	*SE Mean*
LoA		
4	14.5750	0.0640
5	15.6000	0.0640
6	15.6000	0.0640
P. Stage		
EXTRACTN	17.7667	0.0739
HD KNV	15.9000	0.0739
KNIV	13.2333	0.0739
SHREDD	14.1333	0.0739

α = 0.05 significance level

There are two factors included in the analysis, LoA and P.Stage. Both factors are fixed, the LoA factor has 3 levels with values 4, 5, and 6. The P.Stage factor has four levels with values KNIV, SHREDD, HD KNV and EXTRACN.

In the %brix analysis in Table *4-11*, the effects of LoA and the process stage were assessed. The commonly chosen α-level of 0.05 was chosen and the results indicate the following: The p-value for both the LoA and P. Stage factor given as 0.000 is less than 0.05. Since this is less than the chosen α-level of 0.05, it means the effect of LoA and P. Stage on the juice brix is significant. This implies that, the mean %brix is different for the different LoA and P. Stages. From the modal summary S is 0.128019, R^2 is 99.75%, and adjusted R^2 equals 99.54% which indicates that the model explains 99.75% of the variation in % brix when you use it for prediction. This is good for comparing different % brix models since S is very minimal and R maximum.

From coefficients, both LoA and P.Stage is significant at all levels (p= 0.000 or 0.001) since they are all less than α=0.05. Consequently, the effect of one predictor does not depend on the value of the other predictor. Also, The VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equation, employing Conventional automation (LoA = 4) in the 4 process stages applicable gives a mean %brix of (15.2583-0.6833+2.5083+0.6417-2.0250 - 1.1250) 14.575%, while SCADA (LoA = 5) and DCS (LoA = 6) results to 15.6% each. This is evidence that SCADA (LoA = 5) and DCS (LoA = 6) are efficient in enhancing the sucrose concentration and consequently the quality of the sugar juice extract.

For relationship analysis, let:

H_o: There is no linear relationship between LoA and %brix (All the population means for the various treatments are equal)

H_1: There exist a functional relationship between LoA and %brix. True if $F_{cal} > F_{crit}$.

Since for LoA, F_{cal} (85.47) > F_{crit} (5.14), H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and %brix. Similarly for P. Stage, F_{cal} (736.46) > F_{crit}, (4.76), thus H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between P.stage and %brix.

Also, from the positively sloped correlation curves with high Pearson's coefficient of 0.75 in Figure *4-14*, the % brix is directly proportional to the LoA.

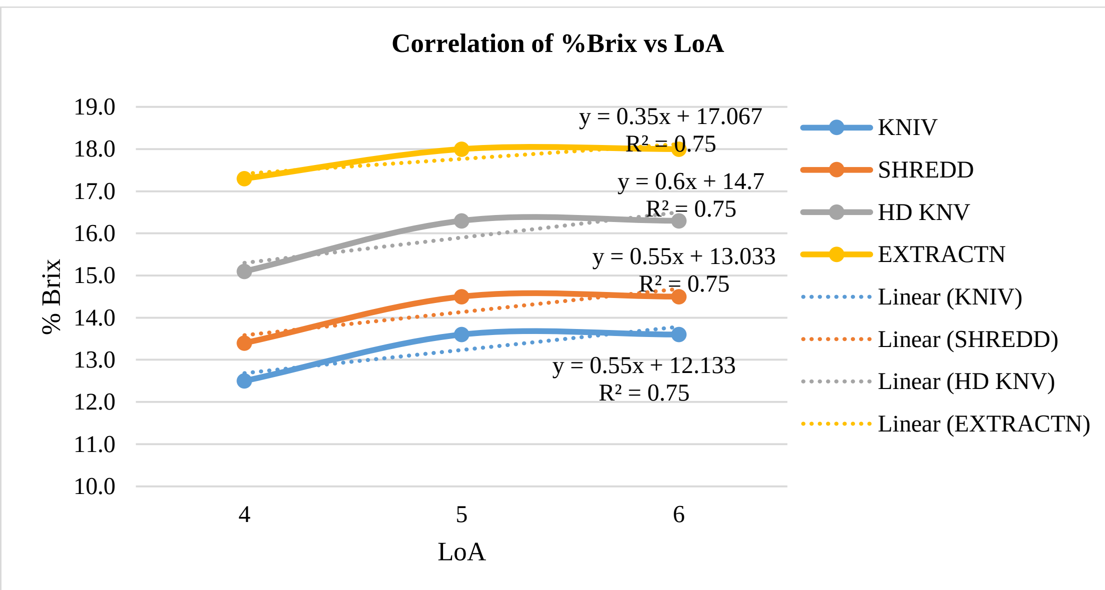

Figure 4-14 Coefficient graph of % brix vs LoA for different P.stages (Source: Field data, 2019)

The brix which represents the percentage by mass of soluble solids in a pure sucrose solution, is relatively high when either LoA 5 or 6 is used. This can be attributed to the precision and accuracy with which parameters affecting the quality of juice extraction are monitored and controlled in real time. Unlike when LoA 4 is employed, the %brix is relatively lower. The higher the % brix in the sugar juice, the higher the sucrose content and consequently the higher the performance of the production quality.

This conforms to Xiao (2017), who observed that the higher the brix of the sugar juice, the higher the sucrose content and consequently the higher the quality of sugar produced. Therefore, LoA 5 or 6 should be introduced in the local industries with the aim of harnessing more sucrose content from the sugar cane fibres as compared to LoA 4.

From Figure 4-15, the sensitivity test for PI on a range of 10% to 95% CI depicts that the residuals appear to follow a straight line. There is no evidence of non-normality, skewness, outliers, or unidentified variables that exists.

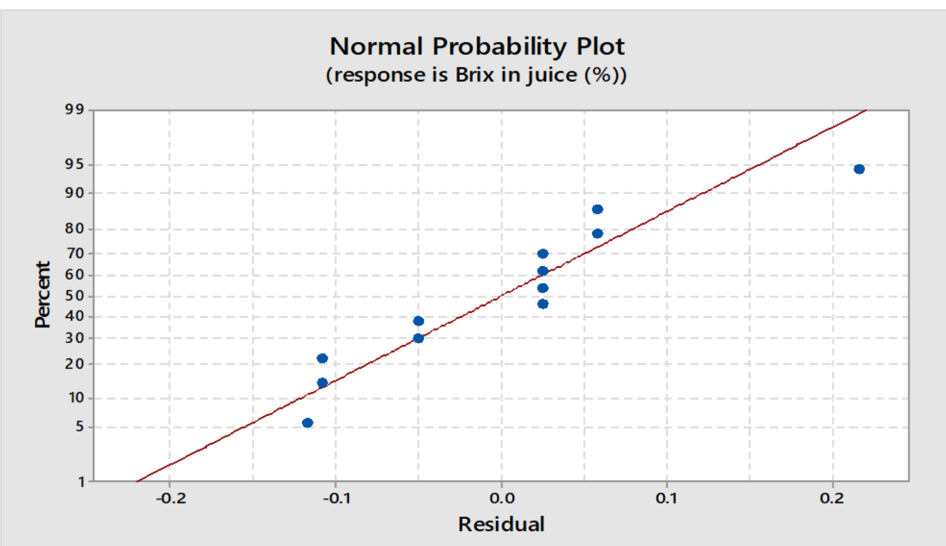

Figure 4-15 Normal probability plot for % Brix in juice (Source: Researcher, 2019)

4.3.3 %pol

The %pol was measured in the laboratory using polarimeter for the samples of juices collected at the relevant process stages. For the experiment conducted, %pol for three different levels of automation (LoA 4, LoA 5 and LoA 6) was determined in four process stages where it was applicable namely KNIV, SHREDD, HD KNV and EXTRACTN as shown in Figure *4-16*.

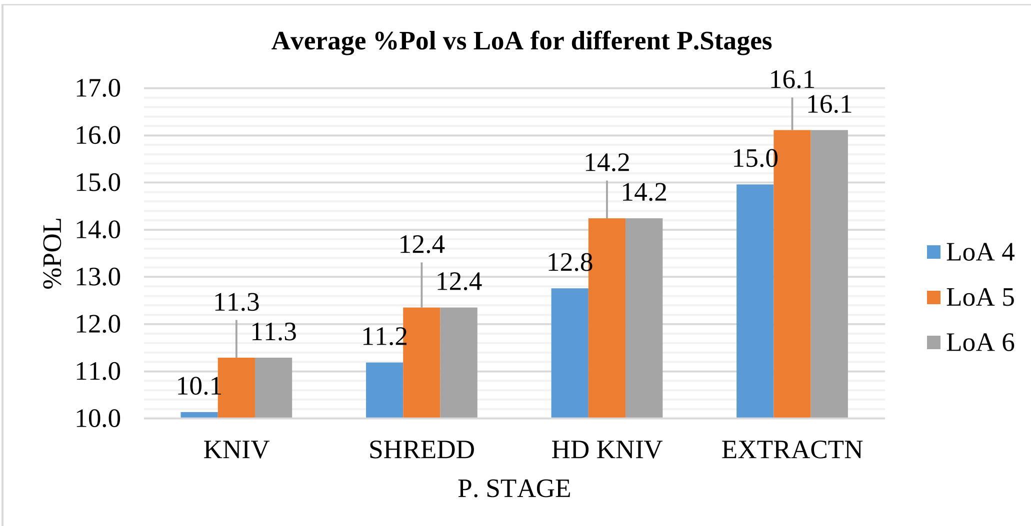

Figure 4-16 %pol graph for different levels of automation (Source: Researcher, 2019)

The conventional automation (LoA 4) recorded a low mean pol value of 15.1% compared to LoA 5 and LoA 6 which recorded a relatively high mean pol value of 16.1% for the final juice extract. The high pol value is as a result of the adoption of HD KNIV stage along the process line when a diffuser which only complies with SCADA or DCS automation systems. In this stage, the cane fibres are further scattered to expose more sucrose which increase the pol% compared to LoA with mill tandems which do not incorporate the HD KNIV.

The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on % pol. There were 7 replicates for each separate treatment levels under investigation.

Table 4-12: General Linear Model: pol (%) versus LoA, P. Stage

Factor Information

Factor	*Type*	*Levels*	*Values*
LoA	Fixed	3	4, 5, 6
P. Stage	Fixed	4	EXTRACTN, HD KNV, KNIV, SHREDD

Analysis of Variance

Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*F-Crit*
LoA	2	3.7996	8.42%	3.7996	1.8998	124.38	0.000	4.76
P. Stage	3	41.2318	91.38%	41.2318	13.7439	899.81	0.000	5.14
Error	6	0.0916	0.20%	0.0916	0.0153			
Total	11	45.1231	100.00%					

Model Summary

S	*R-sq*	*R-sq(adj)*	*PRESS*	*R-sq(pred)*
0.123589	99.80%	99.63%	0.366582	99.19%

Coefficients

Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*
Constant	13.1017	0.0357	(13.0144, 13.1890)	367.23	0.000	
LoA						
4	-0.7958	0.0505	(-0.9192, -0.6723)	-15.77	0.000	1.33
5	0.3979	0.0505	(0.2744, 0.5214)	7.89	0.000	1.33
6	0.3979	0.0505	(0.2744, 0.5214)	7.89	0.000	*
P. Stage						
EXTRACTN	2.6842	0.0618	(2.5330, 2.8354)	43.44	0.000	1.50
HD KNV	0.6490	0.0618	(0.4978, 0.8002)	10.50	0.000	1.50
KNIV	-2.1972	0.0618	(-2.3484, -2.0460)	-35.56	0.000	1.50
SHREDD	-1.1360	0.0618	(-1.2872, -0.9848)	-18.38	0.000	*

Regression Equation

pol(%) = 13.1017 - 0.7958 LoA_4 + 0.3979 LoA_5 + 0.3979 LoA_6
+ 2.6842 P. Stage_EXTRACTN+ 0.6490 P. Stage_HD KNV
- 2.1972 P. Stage_KNIV - 1.1360 P. Stage_SHREDD

Means

Term	*Fitted Mean*	*SE Mean*
LoA		
4	12.3059	0.0618
5	13.4995	0.0618
6	13.4995	0.0618
P. Stage		

EXTRACTN	15.7858	0.0714
HD KNV	13.7506	0.0714
KNIV	10.9045	0.0714
SHREDD	11.9657	0.0714

α = 0.05 significance level

In Table *4-12*, there are two factors included in the analysis, LoA and P.Stage. Both factors are fixed, the LoA factor has 3 levels with values 4, 5, and 6. The P.Stage factor has four levels with values KNIV, SHREDD, HD KNV and EXTRACN.

In the %pol analysis, the effects of LoA and the process stage were assessed. The commonly chosen α-level of 0.05 was chosen and the results indicate the following: The p-value for the LoA and P. Stage factor given as 0.000 and 0.000 respectively are less than 0.05. Since this is less than the chosen α-level of 0.05, it means the effect of LoA and P. Stage on the juice pol is significant. This implies that, the mean %pol is different for the different LoA and P.Stages. From model summary, S is 0.326261, R^2 is 99.81%, and adjusted R^2 equals 99.67% which indicates that the model explains 99.81% of the variation in % pol when you use it for prediction. This is good for comparing different % pol models since S is very minimal and R maximum.

From the coefficients, all the levels of both LoA and P.Stage depicted p-values less than α=0.05.therfore, the analysis is significant and consequently, the effect of one predictor does not depend on the value of the other predictor. Also, The VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equation, employing Conventional automation (LoA = 4) a mean %pol of 12.3%, while SCADA (LoA = 5) and DCS (LoA = 6) results to 13.5% each. This is evidence that SCADA (LoA = 5) and DCS (LoA

= 6) are efficient in enhancing the concentration of sucrose concentration and consequently the quality of the sugar juice extract.

For relationship analysis, let:

H_o: There is no linear relationship between LoA and %pol (All the population means for the various treatments are equal)

H_1: There exist a functional relationship between LoA and %pol. True if $F_{cal} > F_{crit}$.

Since for LoA, F_{cal} (124.38) > F_{crit} (4.76), H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and %brix. Similarly for P. Stage, F_{cal} (899.81) > F_{crit}, (5.14), thus H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between P.stage and %brix.

Also, from the positively sloped correlation curves with high Pearson's coefficient of 0.75 in Figure *4-17*, the % pol is directly proportional to the LoA.

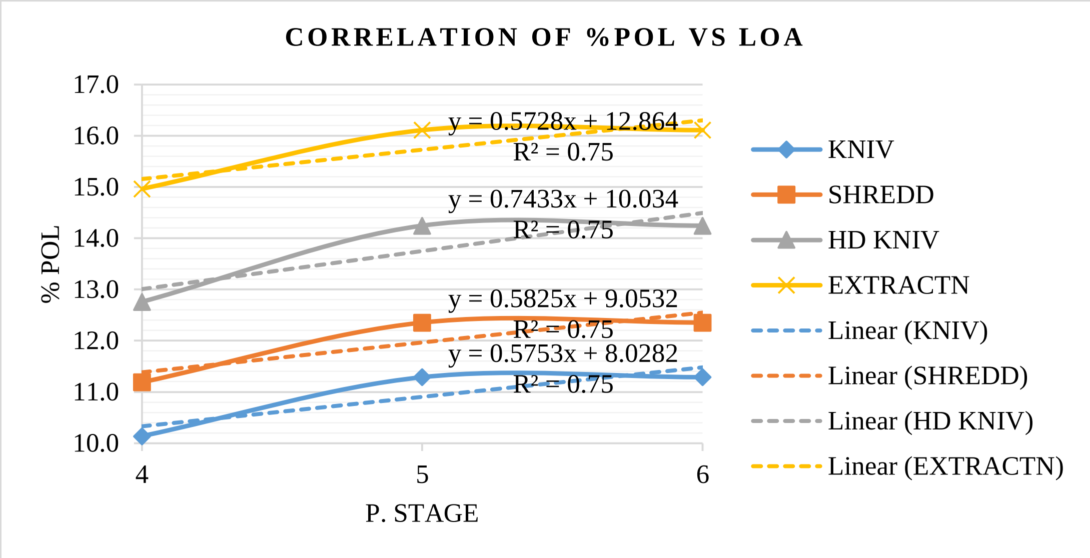

Figure 4-17 Coefficient graph of % pol vs LoA for different P.stages (Source: Field data, 2019)

The pol represents the apparent sucrose content of any substance determined by a polarisation method and expressed as a percentage by mass or in degrees Z (°Z), is relatively high when either LoA 5 or 6 is used. This can be attributed to the precision and accuracy with which parameters affecting the quality of juice extraction are monitored and controlled in real time. Unlike when LoA 4 is employed, the %pol is relatively lower. The higher the % pol in the sugar juice, the higher the sucrose content and consequently the higher the performance of the production quality.

This conforms to Xiao (2017), who observed that the higher the pol of the sugar juice, the higher the sucrose content and consequently the higher the quality of sugar produced. Therefore, LoA 5 or 6 should be introduced in the local industries with the aim of harnessing more sucrose content from the sugar cane fibres as compared to LoA 4.

From Figure 4-18, the sensitivity test for %pol on a range of 95% CI depicts that the residuals appear to follow a straight line. There is no evidence of non-normality, skewness, outliers, or unidentified variables that exists.

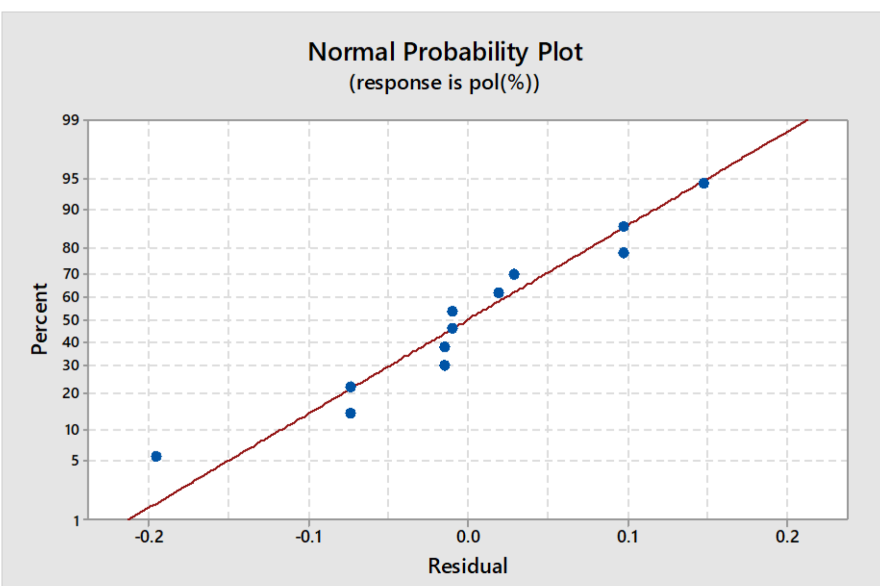

Figure 4-18: Normal probability plot for %pol (Source: Researcher, 2019)

4.3.4 Apparent purity of the sugar juice extracted

The purity was calculated as the quotient of pol to brix of the sugar juice at the final stage of the extraction and the result depicted by Figure *4-19*.

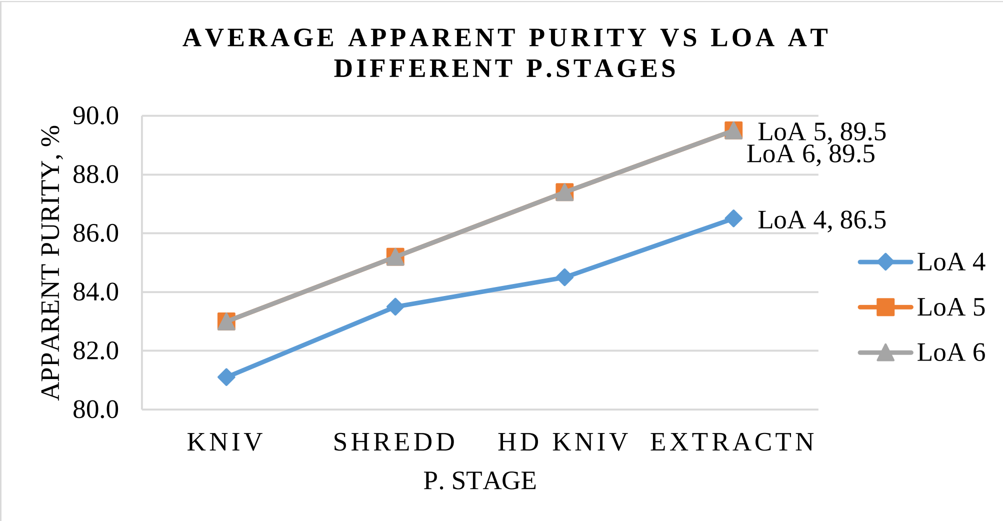

Figure 4-19: Apparent purity graph of the sugar juice extracted (Source: Researcher, 2019)

The graph indicates that the purity of sugar juice when conventional automation (LoA 4) is employed is relatively low with a mean value of 86.5% compared to when SCADA and DCS are used where a mean purity level of 89.6% was realised. Therefore, with LoA 5 and 6, the purity of the sugar will be high as described and this consequently gives high quality of the sugar production compared to the conventional automation.

The experiment was a randomized block with two factors (LoA and P.Stage) investigated on three key indicators that affect the quality of sugar produced through the purity of the juice extract namely PI, % brix and pH variability. There were 7 replicates for each separate treatment levels under investigation. From Eq. 3-15, the quality production index was evaluated and recorded as shown in Table *4-13* and Figure *4-20*

Table 4-13: Quality production parameter indices vs LoA

Parameters for quality production	**Conventional automation LoA 4**	**SCADA LoA5**	**DCS LoA6**
Preparation index (PI), y_{41}	77.0	80.7	83.0
Brix (%), y_{43}	14.6	15.6	15.6
pol (%), y_{42}	12.3	13.5	13.5
Apparent purity, y_{44}	84.2	86.3	86.3
Quality production index, y_4	**81.3**	**84.0**	**85.0**

$$Quality\ production\ index\ (y_4) = \frac{2}{5}\left(\frac{\sum_1^3 y_{41}}{3}\right) + \frac{3}{5}\left(\frac{\sum_1^4 y_{44}}{4}\right);\ y_{44} = \left(\frac{y_{43}}{y_{42}}\right)x100\%$$

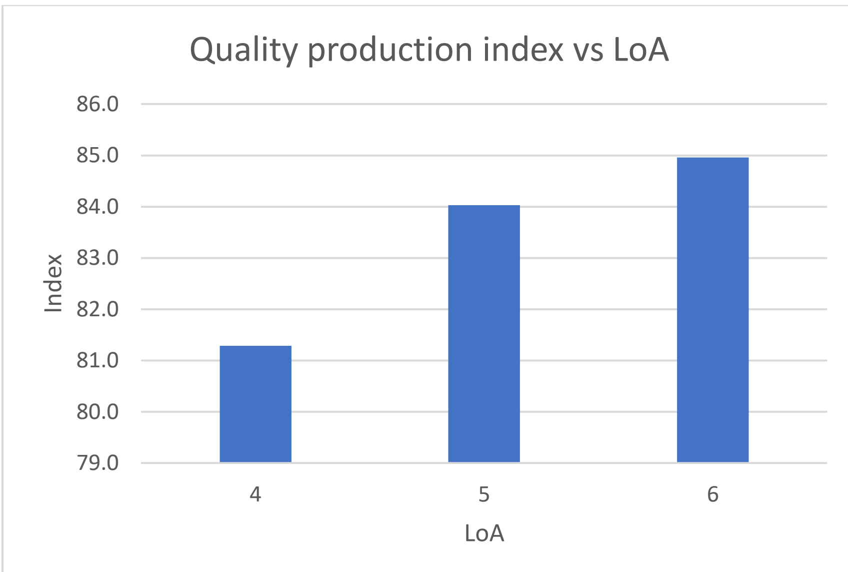

Figure 4-20: Quality production index vs LoA

Table *4-13* indicate that the 4 quality production parameters increases when the LoA increases. Furthermore in Figure *4-20*, quality production index increased from LoA 4 through LoA 5 to LoA 6, suggesting that LoA 6 is the optimum for attaining improved quality production due to its high changeover in quality parameters. This concurs with Martinez et.al, 2001 who alluded that for optimum quality, the responsible manufacturing indicators must increase. Since $\mu_{LoA\ 4} \neq \mu_{LoA\ 5} \neq \mu_{LoA\ 6}$ it can be asserted that there is a relationship between LoA and quality production.

The analysis is summarized in both the probability plot and summarized ANOVA table shown.

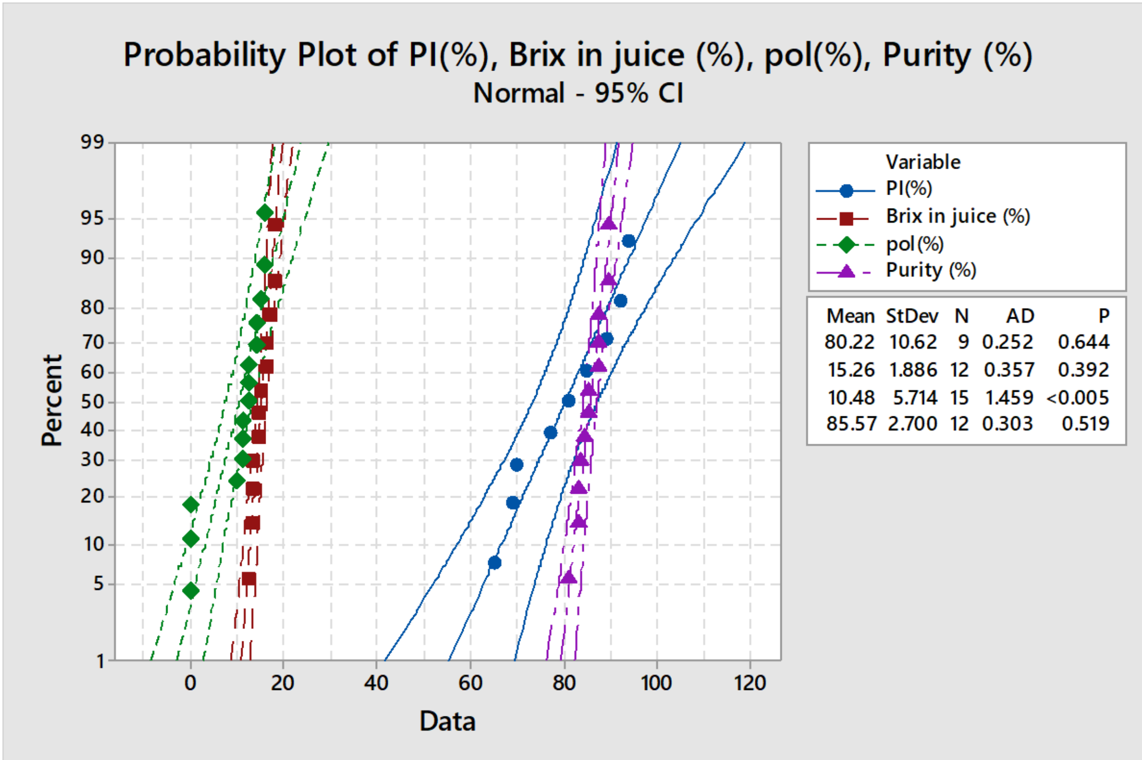

Figure 4-21 Probability plot of PI, % brix, % pol and apparent purity for 5 - 95% CI (Source, Field data, 2019)

Table 4-14 Analysis for impact of lean automation on quality sugar production (Source: Field data, 2019)

Description	**LoA**	**No. of P.stages**	**Mean**	**Variance**	**Test for significance (ANOVA)**
PI	LoA 4 LoA 5 LoA 6	3 3 3	77.0% 80.7% 83.0%	144.0 132.3 147.0	F_{Calc} = 29.06 F_{Crit} = 6.94 P-Value = 0.004 α = 0.05 DF = 2 $F_{Calc} > F_{Crit}$ and α > P-Value Com = Significant at 0.05 level
% brix	LoA 4 LoA 5 LoA 6	4 4 4	14.6 15.6 15.6	4.46 3.82 3.82	F_{Calc} = 85.49 F_{Crit} = 5.14 P-Value = 0.000 α = 0.05 DF = 2 $F_{Calc} > F_{Crit}$ and α > P-Value Com = Significant at 0.05 level
% pol	LoA 4 LoA 5 LoA 6	4 4 4	12.3 13.5 13.5	4.40 4.52 4.52	F_{Calc} = 124.38 F_{Crit} = 4.76 P-Value = 0.000 α = 0.05 DF = 2

					$F_{Calc} > F_{Crit}$ and α > P-Value Com = Significant at 0.05 level
Apparent purity	LoA 4 LoA 5 LoA 6	4 4 4	84.15 86.27 86.27	5.04 7.85 7.85	F_{Calc} = 50.2 F_{Crit} = 5.14 P-Value = 0.000 α = 0.05 DF = 2 $F_{Calc} > F_{Crit}$ and α > P-Value Com = Significant at 0.05 level

From both Figure *4-21* and Table *4-14*, the p-values for the LoA given as 0.000 is less than 0.05. This implies that the effect of LoA on the juice purity is significant. Thus, the mean %purity is different for the different LoA. But this also depends on the respective process stages involved. This model explains 99.30% of the variation in % purity when you use it for prediction. This is good for comparing different % purity models since R^2 is maximum.

From the coefficients, all the levels of both LoA and P.Stage depicted p-values less than α=0.05. Therefore, the analysis is significant and consequently, the effect of one predictor does not depend on the value of the other predictor. Also, The VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equations, employing Conventional automation (LoA = 4) in the 4 process stages applicable gives a mean %purity of 84.15%, while SCADA (LoA = 5) and DCS (LoA = 6) results to 86.275% each. This is evidence that SCADA (LoA = 5) and DCS (LoA = 6) are efficient in enhancing the sucrose concentration and consequently the quality of the sugar juice extract.

This implies that LoA 5 or 6 is the optimum automation level for high juice purity in a sugar industry if quality production is to be achieved. From the probability plot in Figure *4-21*, all the three parameters have $p < 0.05$. Therefore, results are significant.

The quality of sugar production will depend on the quality of sugar juice. This is consequently indicated by the apparent purity of the juice extract which depends on %brix, %pol and the preparation index (PI). Quality of the sugar is determined by the apparent purity of the sugar juice extracted, and this depends further on the nature of the technology employed which dictates the process parameters. A high quality sugar is characterized by a high preparation index (PI), high sugar concentration in the juice (%brix) and (%pol). From *Table*, PI is only measured at the knives, shredders and (High density knives for LoA 5 and 6) while brix and moisture at the extraction stage. In all the stages level 6 recorded the highest PI and Brix values of 94% and 18%, and the lowest moisture in the bagasse of 40% at HD KNV and Extraction stages, compared to level 4 with PI and Brix values of 77% and 17.3% at Shredder and Extraction stages respectively and a moisture content of 50%. This is because in level 6, the process parameters desired to optimize the process, are well monitored and regulated by the real time sensors. Also, the diffusion extraction that is usually fully automated provides an optimum means of extracting all the sucrose from the fibers compared to the mill tendons that are mainly monitored remotely. The diffuser has sensors and actuators that detects a variation in the process parameter and initiate appropriate corrective measure to maintain the optimum values. Level 6 involved the use of these sensing devices, visual and audio devices for communication. Thus adopting levels 5 or 6 the product, the apparent quality of the juice extract will be high, and consequently quality will be achieved and this will provide competitiveness in the sugar industry. This is due to negligible variability in the set process parameters when using LoA 5 or 6, as the response to changes is rapid compared to when LoA 4 is employed. It is therefore observed that the purity is directly proportional to the polarization and inversely proportional to the brix.

This concurs with Xiao (2017) in his analysis of sugar cane juice quality indexes who found out that, the effect of polarization (%Pol) and %brix on sucrose content is directly proportional to the apparent purity of the juice. Further, sucrose content is the quotient of %pol to %brix, thus it increases with an increase in %pol and decreases with an increase %brix. This in turn influences the effect of apparent purity and %brix on the sucrose content while maintaining %pol in that, sucrose content decreases with an increase in apparent purity and %brix.

In addition, this conforms to Six Sigma theory that emphasizes on reduction of variations to enhance processes. Through the help of statistical techniques, it is possible to forecast the process outcomes. If unexpected outcome is noticed, then advanced control tools can be used to explain the phenomenon. In relation to lean automation, the integration of lean and proper levels of automation provides a suitable advanced control tool to best understand and identify parameters that affect or vary the process, and hence the overall performance of the organization (Dave, 2002).

The relatively high %pol, %brix and %purity indices were recorded by LoA 5 (SCADA) and 6 (DCS) as compared to LoA 4. Therefore, levels 5 or 6 of automation will provide an optimum apparent purity of juice and subsequent steadfast quality production that will be competitive and this will render the sugar industries sustainable in their production.

4.4 Potential of lean automation in minimizing resource wastage.

Resources are the inputs and controls that are involved in the transformation of raw materials to the final products. These resources are acquired by the industry at a cost. This necessitates the need to reduce wastage of these resources in the industry if profits and quality products are to be realized. From Fig 2-1, it is noted that the effectiveness of an automated lean manufacturing to minimize wastage is subject to the extent with which the resources utilization is reduced. This was demonstrated by the power consumption, set up time and the process cycle time. The lower the power consumption, set up time and cycle time, the better LoA in minimization of wastage within the manufacturing line and vice versa.

4.4.1 Power consumption

The power consumption was measure in relation to the power rating of the machines involved when the respective level of automation is employed at a given process stage. For this experiment, power consumption for 3 different level of automation (LoA 4, LoA 5 and LoA 6) was determined in 8 process stages where it was applicable as shown in Figure *4-22*.

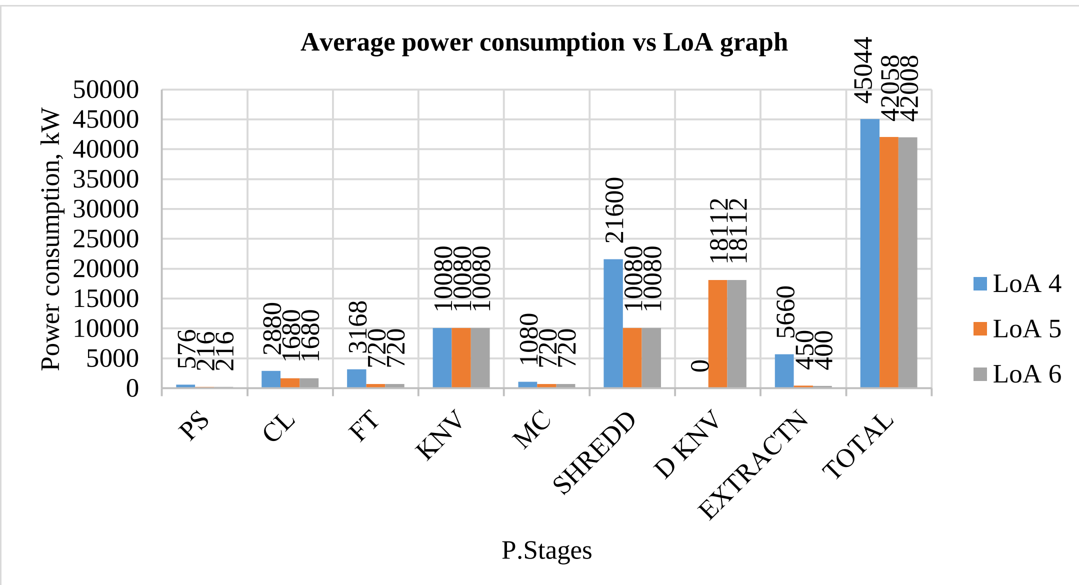

Figure 4-22 Power consumption graph for LoA and P.Stage (Source: Researcher, 2019)

From *Figure 4-22*, the rate of power consumption of the entire juice extraction process line, when employing conventional automation (LoA 4), is relatively higher with a total of 45,044 kW compared to when SCADA (LoA 5) or DCS (LoA 6) are used with a total power consumption of 42,058 kW and 42,008 kW respectively. Conventional automation is characterized by the use of mill tandems which do not require a high PI hence there being no HD KNIV stage, but still the total power consumption is high. Whereas LoA 5 and 6 are associated with the use of diffuser but can also be incorporated with mills. The high power consumption could be as a result of the machines at respectful stages drawing power without performing meaningful work due to unprecise mechanisms of sensing, monitoring and regulating the process parameter. It is therefore evident that, the higher the level of automation the lower the power consumption.

The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on PI. There were 7 replicates for each separate treatment levels under investigation.

Table 4-15 ANOVA for total power (Kw/day) vs LoA, P. Stage (Source: Research, 2019)

Factor Information								
Factor	*Type*	*Levels*	*Values*					
LoA	Fixed	3	4, 5, 6					
P. Stage	Fixed	8	CL, EXTRACTN, FT, HD KNV, KNIV, MC, SHREDD, WB					
Analysis of Variance								
Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*Fcrit*
LoA	2	6788955	0.70%	42493597	21246799	3.98	0.045	3.74
P. Stage	7	889795227	92.11%	889795227	127113604	23.82	0.000	2.76
Error	13	69379339	7.18%	69379339	5336872			
Total	22	965963522	100.00%					
Model Summary								
R-sq	*R-sq(adj)*	*PRESS*	*R-sq(pred)*					
92.82%	87.85%	210311742	78.23%					
Coefficients								
Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*		
Constant	6260	488	(5205, 7314)	12.82	0.000			
LoA								
4	2012	713	(472, 3552)	2.82	0.014	1.42		
5	-1003	679	(-2469, 463)	-1.48	0.163	1.38		
6	-1009	679	(-2475, 457)	-1.49	0.161	*		
P. Stage								
CL	-4180	1254	(-6889, -1471)	-3.33	0.005	1.77		

EXTRACTN	-4090	1254	(-6799, -1381)	-3.26	0.006	1.77
FT	-4724	1254	(-7433, -2015)	-3.77	0.002	1.77
KNIV	3820	1254	(1111, 6529)	3.05	0.009	1.77
MC	-5420	1254	(-8129, -2711)	-4.32	0.001	1.77
SHREDD	7660	1254	(4951, 10369)	6.11	0.000	1.77
WB	-5924	1254	(-8633, -3215)	-4.72	0.000	*
Regression Equation						
Total power (Kw/day) = 6260 + 2012 LoA_4 - 1003 LoA_5 - 1009 LoA_6 - 4180 P. Stage_CL - 4090 P. Stage_EXTRACTN - 4724 P. Stage_FT + 12858 P. Stage_HD KNV + 3820 P. Stage_KNIV - 5420 P. Stage_MC + 7660 P. Stage_SHREDD - 5924 P. Stage_WB						
Means						
Term	Fitted Mean	SE Mean				
LoA						
4	8272	900				
5	5257	817				
6	5251	817				
P. Stage						
CL	2080	1334				
EXTRACTN	2170	1334				
FT	1536	1334				
HD KNV	19118	1672				
KNIV	10080	1334				
MC	840	1334				
SHREDD	13920	1334				
WB	336	1334				

α = 0.05 significance level

In analysis of variables in Table *4-15*, the effects of LoA and the process stage were assessed. The commonly chosen α-level of 0.05 was chosen and the results indicate the following: The p-values for the LoA and P. Stage factor given as 0.045 and 0.000 are less than 0.05. Since these are less than the chosen α-level of 0.05, it means the effect of LoA and P. Stage on the power consumption is significant. This implies that, the total power consumption| is different for the different LoA and P.Stages. From model summary, R^2 is 92.82%%, and adjusted R^2

equals 87.85%% which indicates that the model explains 92.82**%** of the variation in % power consumption when you use it for prediction. This is good for comparing different % power consumption models since R is maximum.

From the coefficients, .all the levels of P.Stage depicted p-values less than α=0.05. Therefore, the analysis is significant and consequently, the effect of one predictor does not depend on the value of the other predictor. However, for LoA 5 and 6, the p value are greater than the significant level. This may be attributed to the shredding stage that is only significant when the characteristics of LoA 5 and/or 6 are employed. Also, The VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equation, employing Conventional automation (LoA = 4) in the 4 process stages applicable gives a mean %purity of (6260 + 2012 LoA_4 - 4180 P. Stage_CL- 4090 P. Stage_EXTRACTN - 4724 P. Stage_FT + 12858 P. Stage_HDKNV+ 3820 P. Stage_KNIV- 5420 P. Stage_MC+ 7660 P. Stage_SHR EDD - 5924 P. Stage_WB) 8272kW, while SCADA (LoA = 5) and DCS (LoA = 6) resulted to a mean 5257 kW and 5251 kW respectively. This is evident that SCADA (LoA = 5) and DCS (LoA = 6) are efficient in enhancing power utilisation and consequently minimisation of power consumption for equivalent industrial processes.

For relationship analysis, let:

H_o: There is no linear relationship between LoA and power consumption (All the population means for the various treatments are equal)

H_1: There exist a functional relationship between LoA and power consumption. True if $F_{cal} > F_{crit}$.

Since for LoA, F_{cal} (3.98) > F_{crit}, (3.74), H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and power consumption. Similarly for P. Stage, F_{cal} (23.82) > F_{crit}, (2.76), thus H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between P.stage and power consumption.

Also, from the negatively sloped correlation curves with high Pearson's coefficient of about 0.75 in Figure *4-23* below, the power consumption is inversely proportional to the LoA.

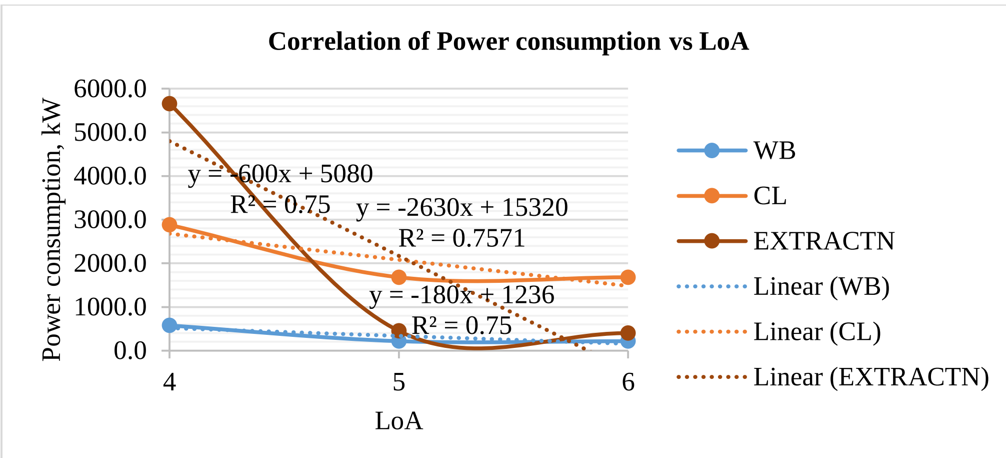

Figure 4-23 Coefficient graph of power consumption vs LoA for different P.stages (Source: Field data, 2019)

Therefore, using LoA 5 or 6, the overall power consumption was lower than the conventional milling technologies. This is attributed to the characteristics of the LoA 5 and 6, where speed variable electro mechanical and hydraulic drives are employed in form of efficient shredders and high density knives compared to the conventional drives used in LoA 4 turbines. Also, LoA 5 and 6 uses a diffuser in the extraction which is exclusively automated with frequency variable drives thus consuming less power while producing quality sugar with adaptive control on parameters. This is contrary to when LoA 4 is employed where mill tandems are withdrawing relatively high power to operate at the expense of low quality and production rate.

This conforms well with Kent and Lewinski (2007) who observed that use of frequency variable electromechanical and hydraulic drives registered an array of advantages compared to the conventional drives by turbines, ranging from better torque and speed control, higher efficiency, higher speed range, higher torque range, easier monitoring, lower maintenance cost. From Figure 4-24, the sensitivity test for power consumption on a range of 95% CI depicts that the residuals appear to follow a straight line. There is no evidence of non-normality, skewness, outliers, or unidentified variables that exists.

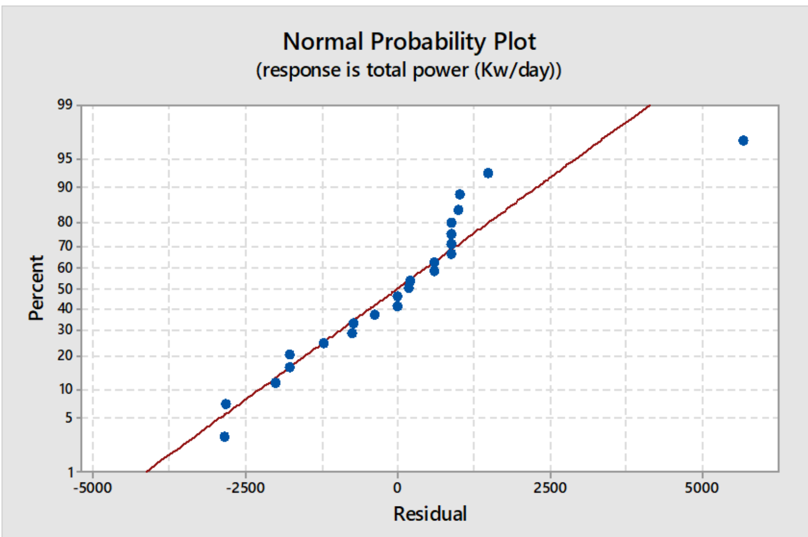

Figure 4-24 Normal probability Plots for total power (Kw/day) for 95% CI (Source: Researcher, 2019)

4.4.2 Set up time

Set up time is the non-value addition time wasted while adjusting the machines to the required operational parameters before initiating a process. The waste cannot be recovered back, thus the need to reduce if not to eliminate. When the set up time is relatively longer for a given process, then the rate of production may be affected leading to a decline in the expected output. The recorded results are shown in Figure *4-25*.

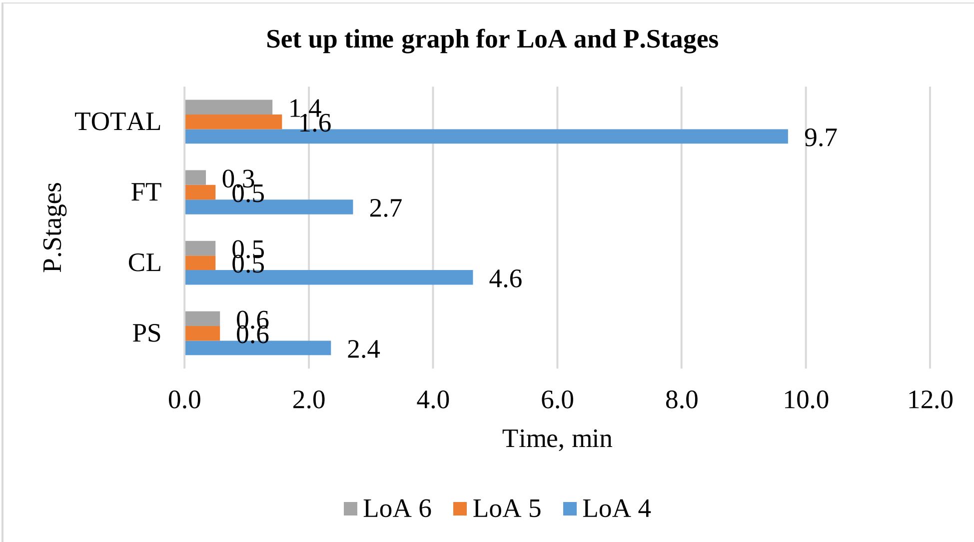

Figure 4-25 Setup time graph for LoA and P.Stages (Source: Researcher, 2019)

Setting up of machines was conducted at three stages namely weigh bridge (WB), Cane Loading (CL) and Feed table and kicker (FT). In all the three stages, LoA 4 recorded the highest setup time whenever the machines needed to be readjusted. In total LoA 4 recorded a set up time of 9.7 min compared to LoA 5 and 6 which recorded a total of 1.6 min and 1.4 min respectively for readjustment. Thus the conventional automations involves long set ups of machines that leads to a high wastage of time resource and consequently, the production rate. Unlike, for SCADA and DCS where the machines are autonomous and the self-align themselves unless there is a technical hitch with the instrumentation.

The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on setup time. There were 7 replicates for each separate treatment levels under investigation.

Table 4-16 ANOVA for setup time (min) versus LoA, P. Stage (Source: Researcher, 2019)

Analysis of Variance								
Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*F-Crit*
LoA	2	15.0532	83.90%	15.0532	7.5266	15.61	0.013	6.94
P. Stage	2	0.9604	5.35%	0.9604	0.4802	1.00	0.446	6.94
Error	4	1.9293	10.75%	1.9293	0.4823			
Total	8	17.9429	100.00%					
Model Summary								
S	*R-sq*	*R-sq(adj)*	*PRESS*	*R-sq(pred)*				
0.694488	89.25%	78.50%	9.76684	45.57%				
Coefficients								
Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*		
Constant	1.405	0.231	(0.762, 2.047)	6.07	0.004			
LoA								
4	1.829	0.327	(0.920, 2.738)	5.59	0.005	1.33		
5	-0.881	0.327	(-1.790, 0.028)	-2.69	0.055	1.33		
6	-0.948	0.327	(-1.857, -0.039)	-2.89	0.044	*		
P. Stage								
CL	0.462	0.327	(-0.447, 1.371)	1.41	0.231	1.33		
FT	-0.238	0.327	(-1.147, 0.671)	-0.73	0.507	1.33		
WB	-0.224	0.327	(-1.133, 0.685)	-0.68	0.532	*		
Regression Equation								
set up time (min) = 1.405 + 1.829 LoA_4 - 0.881 LoA_5 - 0.948 LoA_6 + 0.462 P. Stage_CL - 0.238 P. Stage_FT - 0.224 P. Stage_WB								
Means								
Term	*Fitted Mean*	*SE Mean*						
LoA								
4	3.233	0.401						
5	0.524	0.401						
6	0.457	0.401						
P. Stage								
CL	1.867	0.401						
FT	1.167	0.401						
WB	1.181	0.401						

α = 0.05 significance level

In analysis of variables in Table *4-16*, the effects of LoA and the process stage were assessed. The commonly chosen α-level of 0.05 was chosen and the results indicate the following: The p-value for the LoA factor given as 0.018 is less than 0.05. Since this is less than the chosen α-level of 0.05, it means the effect of LoA on the setup time is significant. This implies that, the total setup time| is different for the different LoA. While for the P.Stage, the p-value of 0.475 is greater than 0.05 thus not significant in explaining set up time. From the model summary, R^2 is 87.45%, and adjusted R^2 equals 74.89% which indicates that the model explains 87.45**%** of the variation in setup time when you use it for prediction. This is good for comparing different set up time models since R is maximum.

From the coefficients, p-values of the constant term and that of LoA 4 are less than $\alpha = 0.05$. Therefore, the analysis is significant and consequently, the effect of one predictor does not depend on the value of the other predictor. However, for LoA 5 and 6, the p value are slightly greater than the significant level, but within the limits. This may be attributed to the few stages chosen for this model. Also, The VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equation, employing Conventional automation (LoA = 4) in the 3 process stages applicable gives a mean setup time of 3.2 min, while SCADA (LoA = 5) and DCS (LoA = 6) resulted to a mean 0.524 min and 0.457 min respectively. This is evident that SCADA (LoA = 5) and DCS (LoA = 6) are efficient in reducing the idling time and consequently resource management and higher production rates.

For relationship analysis, let:

> H_o: There is no linear relationship between LoA and setup time (All the population means for the various treatments are equal)
>
> H_1: There exist a relationship between LoA and setup time. True if $F_{cal} > F_{crit}$.

Since for LoA, F_{cal} (15.61) > F_{crit}, (6.94), H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and PI. On the contrary for P. Stage, F_{cal} (1) > F_{crit} (6.94), thus H_o is not rejected and it is concluded that at 95% confidence level, there is no sufficient evidence that there exist a relationship between P.stage and setup time.

Also, from the negatively sloped correlation curves with high Pearson's coefficient of above 0.75 in Figure *4-26*, the variability in process temperature is directly proportional to the LoA.

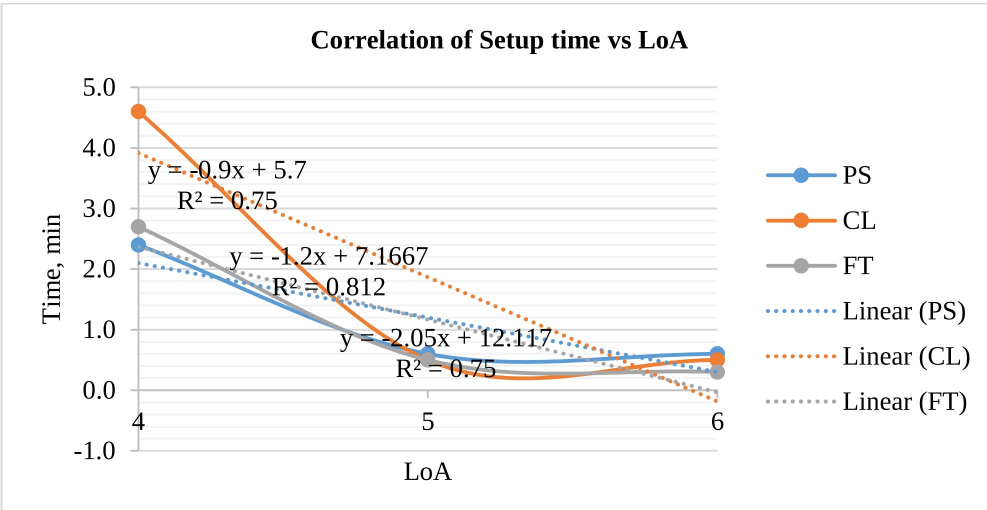

Figure 4-26 Coefficient graph of setup time vs LoA for different P.stages (Source: Field data, 2019)

It can be seen that LoA 5 and 6 have virtually negligible setup involved except when it is after a general plant overhaul. This is as a result of minimum variations in the process parameters due to their real time monitoring and control. The self-regulation minimises the setup and reduce wastages in the production line and consequently improves performance and quality.

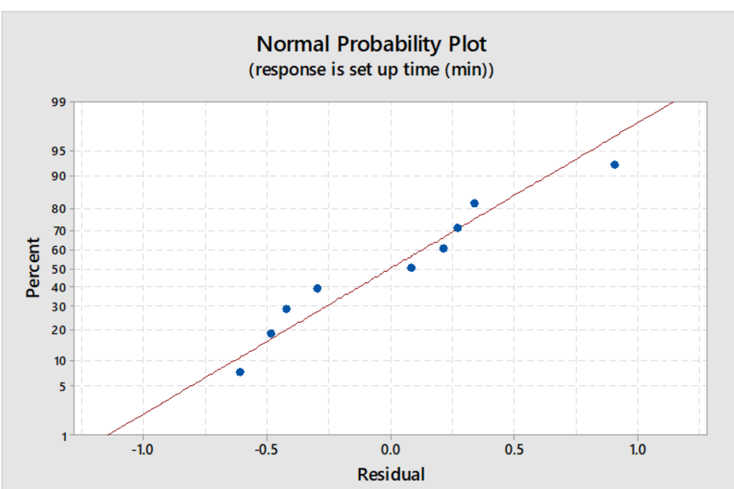

Figure 4-27 Normal probability Plots for set up time (min) for 95% CI (Source: Field data, 2019)

4.4.3 Cycle time

The cycle time is the overall value adding time span required to convert an input to an output. In an industrial set up, the cycle time is dependent on the process activity. Therefore, when the cycle time is relatively longer for a given process, then the rate of production will be reduced as well. This implies that, for an optimum rate of production the cycle time should be at its minimum. The results of the measured cycle time at each process stage is shown in Figure *4-28*.

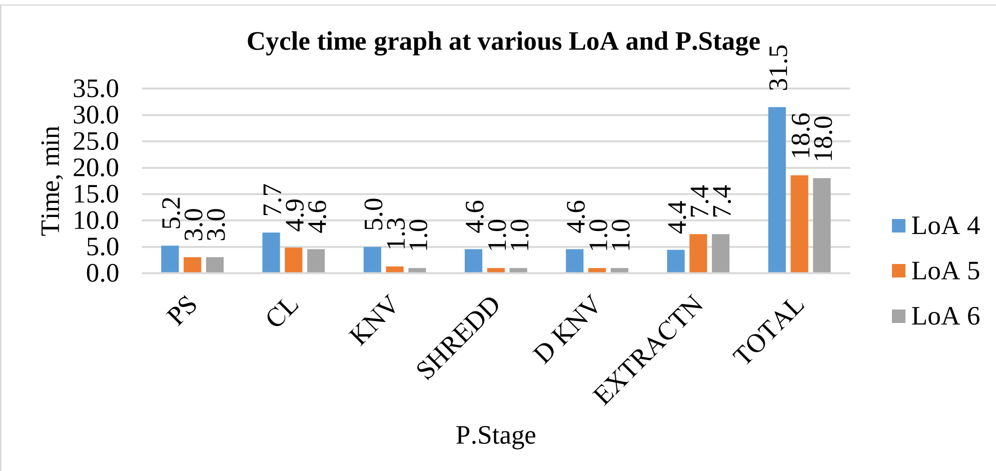

Figure 4-28 Cycle time graph at various LoA and P.Stage (Source: Research, 2019)

Cycle time of processes was conducted at six stages namely weigh bridge (PS), Cane Loading (CL), chopping (KNV), shredding (SHREDD), high density refining(HD KNV) and juice extraction (EXTRACTN). From Figure *4-28*, in all the stages except Extraction, LoA 4 recorded the highest cycle time for any given process stage. In total LoA 4 recorded a cycle time of 31.5 min compared to LoA 5 and 6 which recorded a total cycle time of 18.6 min and 18.0 min respectively for a single batch of sugar production. The cycle time of LoA 4 at the extraction stage is slightly less than that of LoA 5 and 6 because the quantity of batch produced when LoA 4 (mill tandems) is used is slightly lower than that from LoA 5 and 6 (diffuser). Thus the conventional automations involves long cycle times for a given process that leads to a high wastage of time resource and consequently, the production rate. Unlike, for SCADA and DCS where the process are autonomous and the self-alignment of the machines makes the processes to move smoothly, hence saving on time and increasing rate of production.

The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on cycle time. There were 7 replicates for each separate treatment levels under investigation.

Table 4-17 ANOVA for cycle time (min) versus LoA, P. Stage (Source: Researcher, 2019)

Factor Information

Factor	*Type*	*Levels*	*Values*
LoA	Fixed	3	4, 5, 6
P. Stage	Fixed	6	CL, EXTRACTN, HD KNV, KNIV, SHREDD, WB

Analysis of Variance

Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*F Crit*
LoA	2	22.23	22.64%	22.23	11.116	4.47	0.041	4.10
P. Stage	5	51.07	52.02%	51.07	10.215	4.11	0.027	3.33
Error	10	24.87	25.33%	24.87	2.487			
Total	17	98.18	100.00%					

Model Summary

S	*R-sq*	*R-sq(adj)*	*PRESS*	*R-sq(pred)*
1.57705	74.67%	56.93%	80.5812	17.92%

Coefficients

Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*
Constant	3.821	0.372	(2.993, 4.650)	10.28	0.000	
LoA						
4	1.571	0.526	(0.400, 2.743)	2.99	0.014	1.33
5	-0.762	0.526	(-1.933, 0.409)	-1.45	0.178	1.33
6	-0.810	0.526	(-1.981, 0.362)	-1.54	0.155	*
P. Stage						
CL	1.893	0.831	(0.041, 3.745)	2.28	0.046	1.67
EXTRACTN	2.607	0.831	(0.755, 4.459)	3.14	0.011	1.67
HD KNV	-1.488	0.831	(-3.340, 0.364)	-1.79	0.104	1.67
KNIV	-1.488	0.831	(-3.340, 0.364)	-1.79	0.104	1.67
SHREDD	-1.488	0.831	(-3.340, 0.364)	-1.79	0.104	1.67

WB	-0.036	0.831	(-1.888, 1.816)	-0.04	0.967	*
Regression Equation						
cycle time (min) = 3.821 + 1.571 LoA_4 - 0.762 LoA_5 - 0.810 LoA_6 + 1.893 P. Stage_CL + 2.607 P. Stage_EXTRACTN - 1.488 P. Stage_HD KNV- 1.488 P. Stage_KNIV - 1.488 P. Stage_SHREDD - 0.036 P. Stage_WB						
Means						
Term	*Fitted Mean*	*SE Mean*				
LoA						
4	5.393	0.644				
5	3.060	0.644				
6	3.012	0.644				
P. Stage						
CL	5.714	0.911				
EXTRACTN	6.429	0.911				
HD KNV	2.333	0.911				
KNIV	2.333	0.911				
SHREDD	2.333	0.911				
WB	3.786	0.911				

A = 0.05 significance level

In the cycle time analysis Table *4-17*, the effects of LoA and the process stage were assessed. The commonly chosen α-level of 0.05 was chosen and the results indicate the following: The p-value for both the LoA and P. Stage factor given as 0.041 and 0.027 are less than 0.05. Since this is less than the chosen α-level of 0.05, it means the effect of LoA and P. Stage on the cycle time is significant. This implies that, the mean cycle time is different for the different LoA and P. Stages. From the model summary, R^2 is 74.67%, and adjusted R^2 equals 56.93% which indicates that the model explains 74.67% of the variation in cycle time when you use it for prediction. This is good for comparing different cycle time models since R is maximum.

From the coefficients, the VIFs are all less than 5, which indicates that the predictors are not highly correlated. Consequently, the effect of one predictor does not depend on the value of the other predictor. Also, from the regression equation, employing Conventional automation

(LoA = 4) in the 6 process stages applicable gives a mean cycle time of 5.393 min, while SCADA (LoA = 5) and DCS (LoA = 6) results to 3.060 min and 3.012 min respectively. This is evidence that SCADA (LoA = 5) and DCS (LoA = 6) are efficient in reducing the cycle time and consequently the rate of production of the sugar juice extract.

For relationship analysis, let:

H_o: There is no linear relationship between LoA and cycle time (All the population means for the various treatments are equal)

H_1: There exist a relationship between LoA and cycle time. True if $F_{cal} > F_{crit}$.

Since for LoA, F_{cal} (4.24) > F_{crit}, (4.10), H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and cycle. Similarly for P. Stage, F_{cal} (4.63) > F_{crit} (3.33), thus H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between P.stage and cycle time.

Also, from the negatively sloped correlation curves with high Pearson's coefficient of 0.78 in Figure *4-29*, the variability in process temperature is directly proportional to the LoA.

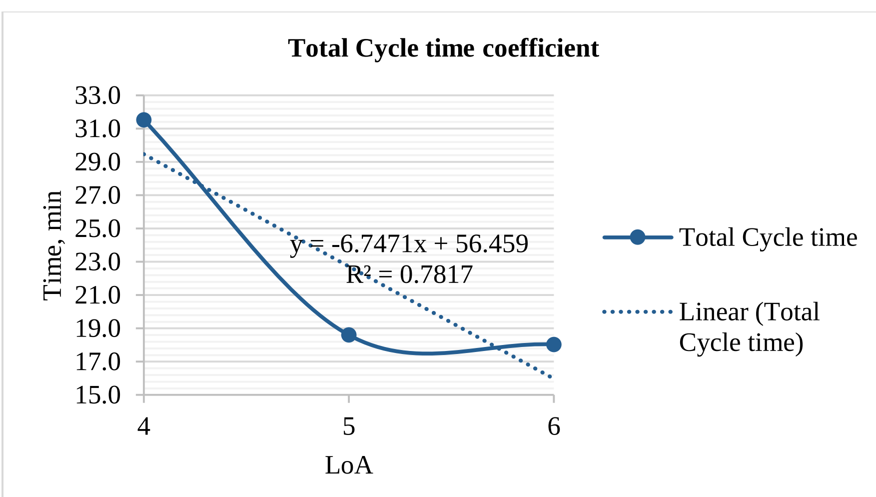

Figure 4-29 Coefficient graph of cycle time vs LoA for different P.stages (Source: Field data, 2019)

The sensitivity test for cycle time on a range of 10% to 95% CI depicts that the residuals appear to follow a straight line and that the results are significant. See Figure *4-30*

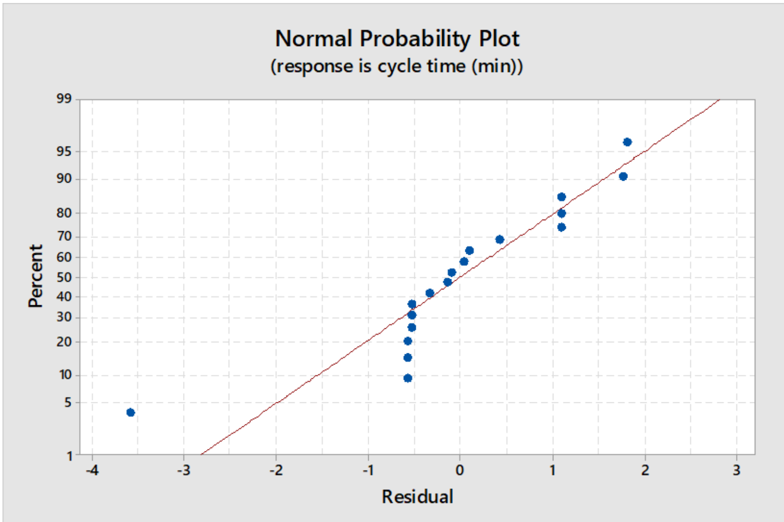

Figure 4-30 Normal probability Plots for cycle time (min) for a range of 10 – 95% CI (Source: Field data, 2019)

4.4.4 Overall rate of resource wastage

The experiment was a randomized block with two factors (LoA and P.Stage) investigated on three key indicators that affect resource utilization through minimized wastages namely power consumption, setup and cycle time. There were 7 replicates for each separate treatment levels under investigation. The results indicated that the cumulative resource utilisation in the Sugar industry reduced when higher levels of automation were implemented. The optimum resourse utilisation was for LoA 6 as shown in Figure *4-31* below.

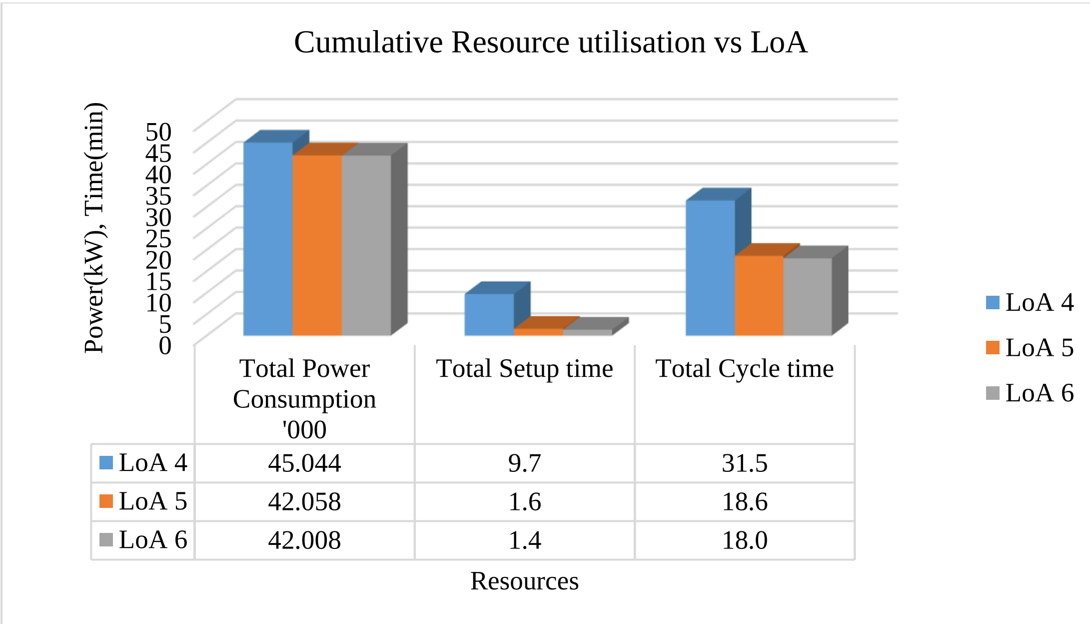

Figure 4-31 Graph of power consumption, cycle time and set up time for different LoA at different process stages (Source: Field data, 2019)

From Eq. 3-13, the resource utilization index was evaluated and recorded as shown in Table *4-18* and Figure *4-32*

Table 4-18 Resource utilization parameter indices vs LoA

Parameters for resource utilization	**Conventional automation LoA 4**	**SCADA LoA5**	**DCS LoA6**
Power consumption (kW), y_{21}	8272.0	5257.0	5251.0
Set up time (min), y_{22}	3.2	0.5	0.5
Cycle time (min), y_{23}	5.4	3.1	3.0
Resource utilization index, y_2	**3311.2**	**2103.6**	**2101.2**

$$\text{Resource utilization index } (y_2) = \frac{2}{5}\left(\frac{\sum_1^7 y_{21}}{7}\right) + \frac{2}{5}\left(\frac{\sum_1^2 y_{22}}{2}\right) + \frac{1}{5}\left(\frac{\sum_1^6 y_{23}}{6}\right)$$

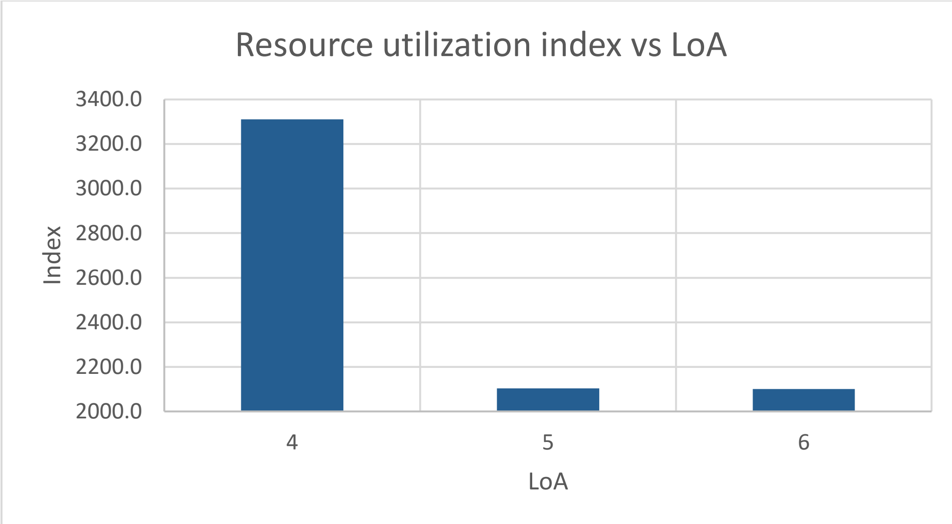

Figure 4-32 Resource utilization index vs LoA

The results in Table *4-18* indicated that the means of 3 resource utilization parameters decreased when the LoA increased. Furthermore, Figure *4-32* revealed that resource utilization index reduced from LoA 4 through LoA 5 to LoA 6, suggesting that either LoA 5 or 6 is the optimum for attaining waste reduction in resources due to their minimal resource utilisation. This concurs with Martinez et.al, 2001 who alluded that for optimum waste reduction, the responsible manufacturing indicators must decrease.

Since $\mu_{LoA\ 4} \neq \mu_{LoA\ 5} \neq \mu_{LoA\ 6}$ it can be asserted that there is a relationship between LoA and waste reduction.

Also, the summarized probability plot and summarized ANOVA table for the variables that affect resource utilization are summarized below.

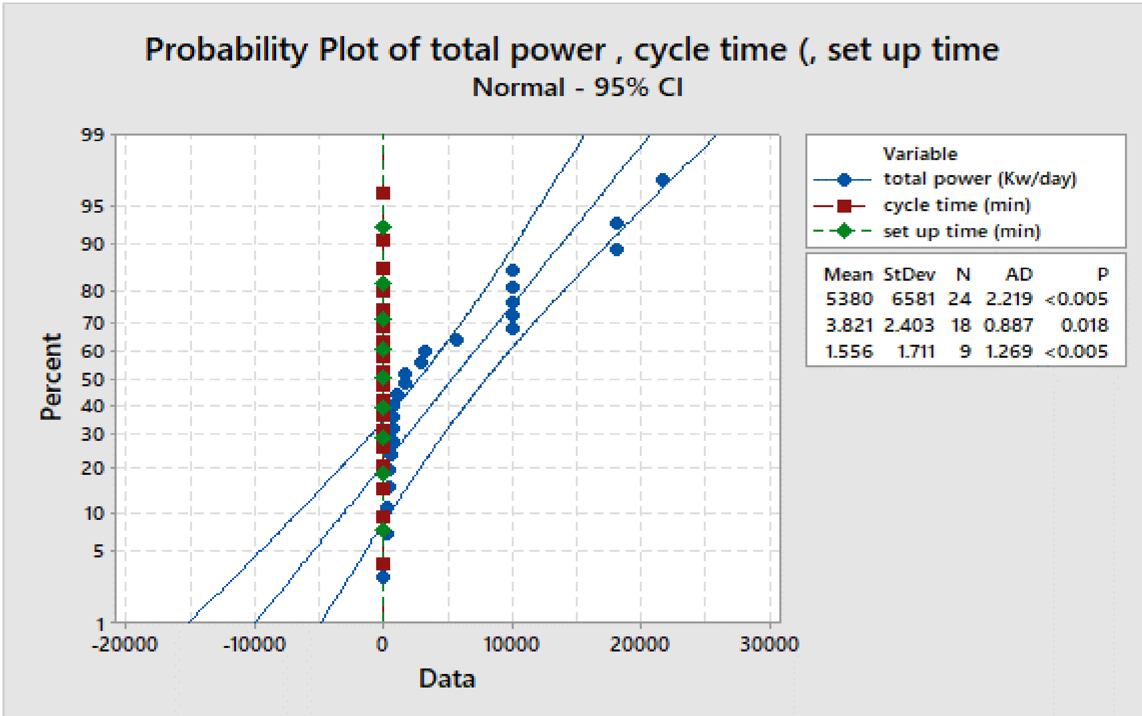

Figure 4-33 Probability plot of total power, cycle time and set up time at 95% CI (Source: Researcher, 2019)

Table 4-19 Analysis for impact of lean automation on minimization of wastage (Source: Field data, 2019)

Description	**LoA**	**No. of P.stages**	**Mean**	**Variance**	**Test for significance (ANOVA)**
Power consumption	LoA 4 LoA 5 LoA 6	8 8 8	8272 5257 5251	52344365.43 44893754.21 44962741.71	F_{Calc} = 3.98 F_{Crit} = 3.74 P-Value = 0.045 α = 0.05 DF = 2 $F_{Calc} > F_{Crit}$ and $\alpha >$ P-Value Com = Significant at 0.05 level
Setup time	LoA 4 LoA 5 LoA 6	3 3 3	3.23 0.53 0.47	1.423 0.003 0.023	F_{Calc} = 15.61 F_{Crit} = 6.94 P-Value = 0.013 α = 0.05 DF = 2 $F_{Calc} > F_{Crit}$ and $\alpha >$ P-Value Com = Significant at 0.05 level
Cycle time	LoA 4 LoA 5 LoA 6	4 4 4	12.3 13.5 13.5	4.40 4.52 4.52	F_{Calc} = 4.47 F_{Crit} = 4.10 P-Value = 0.041 α = 0.05 DF = 2 $F_{Calc} > F_{Crit}$ and $\alpha >$ P-Value Com = Significant at 0.05 level

From both Figure *4-33* and Table *4-19*, wastage in the sugar processing was depicted by three variables namely: power consumption, cycle time and set up time. The rate of power consumption of the entire juice extraction process line when employing conventional automation (LoA 4) is relatively higher with a total of 45044 kW compared to when SCADA (LoA 5) or DCS (LoA 6) are used with a total power consumption of 42058 kW and 42008 kW respectively. Conventional automation is characterized by the use of mill tandems which do not require a high PI hence there being no shredding stage, but still the power consumption is high. Whereas LoA 5 and 6 are associated with the use of diffuser but can also be incorporated with mills. The high power consumption could be as a result of the machines at respectful stages drawing power without performing meaningful work due to unprecise mechanisms of sensing, monitoring and regulating the process parameter.

Therefore, using LoA 5 or 6, the overall power consumption was lower than the conventional milling technologies. This is attributed to the characteristics of the LoA 5 and 6, where speed variable electro mechanical and hydraulic drives are employed in form of efficient shredders and high density knives compared to the conventional drives used in LoA 4 turbines. Also, LoA 5 and 6 uses a diffuser in the extraction which is exclusively automated with frequency variable drives thus consuming less power while producing quality sugar wit adaptive control on parameters. This is contrary to when LoA 4 is employed where mill tandems are withdrawing relatively high power to operate at the expense of low quality and production rate. This conforms well with Kent and Lewinski (2007) who observed that use of frequency variable electromechanical and hydraulic drives registered an array of advantages compared to the conventional drives by turbines, ranging from better torque and speed control, higher efficiency, higher speed range, higher torque range, easier monitoring, lower maintenance cost.

Setting up of machines was conducted at three stages namely weigh bridge (PS), Cane Loading (CL) and Feed table and kicker (FT). In all the three stages, LoA 4 recorded the highest setup time whenever the machines needed to be readjusted. In total LoA 4 recorded a set up time of 9.7 min compared to LoA 5 and 6 which recorded a total of 1.6 min and 1.4 min respectively for readjustments. It can be seen that LoA 5 and 6 have virtually negligible setup involved except when it is after a general plant overhaul. This is as a result of minimum variations in the process parameters due to their real time monitoring and control. The self-regulation minimises the setup and reduce wastages in the production line and consequently improves performance and quality. This is a similar case with cycle time.

Since, levels 5 and 6 of automation utilizes the efficient shredders and VSD that consume less power compared to level 4 that uses high torque knives and CSD. Hence, more power required with conventional level of automation. Consequently, this will ultimately increase both the lead and set up times and thus reducing production in LoA 4. Thus, sugar industries have a potential to adopt either SCADA (LoA 5) or DCS (LoA 6).

This conforms to Ali et.al 2011, who confirmed that productivity is related to value adding activities in the manufacturing transformation process. Thus, any activity not adding value is regarded as a waste. It is therefore, essential to minimize these resource wastes if productivity is to improve. This is in line with the theory of waste elimination which emphasizes on the reduction of non-value adding activities. The probability of the three parameters shows $p < 0.05$.

4.5 Continuous improvements in lean manufacturing.

Continuous improvement also known as Kaizen or Toyota technology is a commitment by firms to utilize small and ongoing positive changes in reaping transformation in manufacturing with the aim of lowering defects, elimination of wastes, increase productivity, promotion of innovation and enhance employee satisfaction. Continuous improvement encompasses identification of threats and opportunities, propose solutions, implementation of the solutions and lastly monitoring and evaluation. In relation to this study, continuous improvement was indicated by the rate of production of the sugar juice extract, and results were as shown in Figure *4-34*

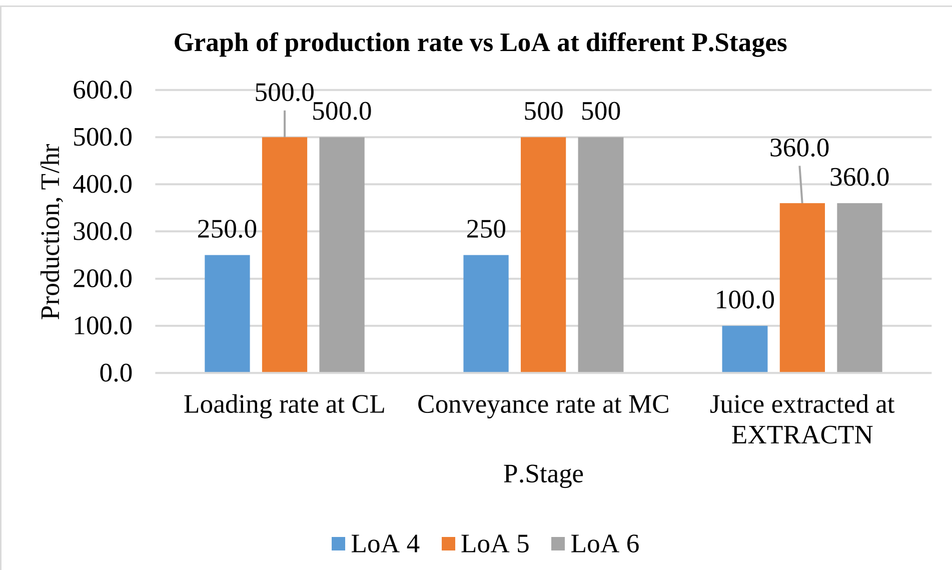

Figure 4-34 Graph of production rate (Source: Researcher, 2019)

From the graph in Figure *4-34*, LoA 4 recorded the least loading rate, conveyance rate and the rate of juice extraction for a given production batch. With a loading rate of 250 T/h, the extracted juice was 100 T/h. Comparing this to the rate of production by LoA 5 and 6 which of 500 T/h each for loading and conveying that yielded juice at the rate of 360T/h, then it can be observed that LoA 5 and 6 which utilizes SCADA or DCS on a diffuser provides a noticeable improvement in the entire rate of production of the sugar. Thus, the optimum option to be adopted in the sugar industries if increased production is to be realized.

The experiment was a randomized block with two factors (LoA and P.Stage) being investigated on PI. There were 7 replicates for each separate treatment levels under investigation. From Eq. 3-14, continuous improvement index was evaluated and recorded as shown in Table *4-20* and Figure *4-35* below.

Table 4-20 Rate of sugar juice extraction vs LoA

Parameters for continuous improvement	**Conventional automation LoA 4**	**SCADA LoA 5**	**DCS LoA 6**
Mean Juice extraction, y_{31}	175.0	430.0	430.0
Continous improvement index, y_3	**175.0**	**430.0**	**430.0**

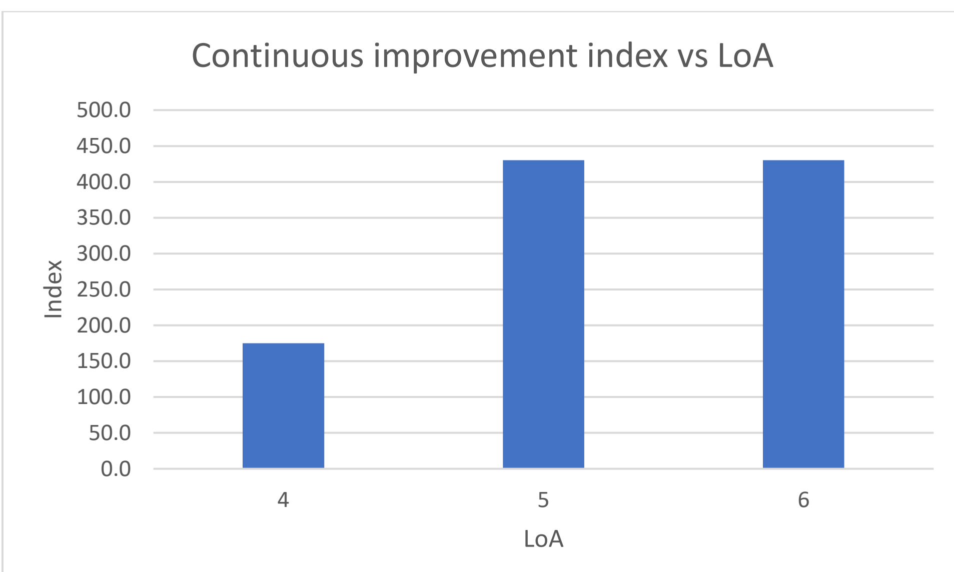

Figure 4-35 Continuous improvement index vs LoA

The results in Table *4-20* indicated that the rate of production parameters increased when the LoA increased. Furthermore, Figure *4-35* revealed that continuous improvement index increased from LoA 4 through LoA 5 to LoA 6, suggesting that either LoA 5 or 6 is the optimum for attaining higher rates of sugar production. This concurs with Martinez et.al, 2001 who alluded that for optimum production, the responsible manufacturing indicators must increase.

Since $\mu_{LoA\ 4} \neq \mu_{LoA\ 5} \neq \mu_{LoA\ 6}$ it can be asserted that there is a relationship between LoA and waste reduction.

Also, the summarized probability plot and summarized ANOVA table for the variables that affect resource utilization are summarized below.

The linear model for the production rate was analyzed as shown in the table below.

Table 4-21 General Linear Model for Rate of production (T/h) versus LoA, P. Stage (Source: Researcer, 2019)

Factor Information								
Factor	*Type*	*Levels*	*Values*					
LoA	Fixed	3	4, 5, 6					
P. Stage	Fixed	2	CL, EXTRACTN					
Analysis of Variance								
Source	*DF*	*Seq SS*	*Contribution*	*Adj SS*	*Adj MS*	*F-Value*	*P-Value*	*Pcrit*
LoA	2	86700	73.76%	86700.0	43350.0	2601.00	0.000	6.94
P. Stage	1	30817	26.22%	30816.7	30816.7	1849.00	0.001	6.94
Error	2	33	0.03%	33.3	16.7			
Total	5	117550	100.00%					
Model Summary								
S	*R-sq*	*R-sq(adj)*	*PRESS*	*R-sq(pred)*				
4.08248	99.97%	99.93%	300	99.74%				
Coefficients								

Term	*Coef*	*SE Coef*	*95% CI*	*T-Value*	*P-Value*	*VIF*
Constant	345.00	1.67	(337.83, 352.17)	207.00	0.000	
LoA						
4	-170.00	2.36	(-180.14, -159.86)	-72.12	0.000	1.33
5	85.00	2.36	(74.86, 95.14)	36.06	0.001	1.33
6	85.00	2.36	(74.86, 95.14)	36.06	0.001	*
P. Stage						
CL	71.67	1.67	(64.50, 78.84)	43.00	0.001	1.00
EXTRACTN	-71.67	1.67	(-78.84, -64.50)	-43.00	0.001	*
Regression Equation						
Rate of production(T/h) = 345.00 - 170.00 LoA_4 + 85.00 LoA_5 + 85.00 LoA_6 + 71.67 P. Stage_CL - 71.67 P. Stage_EXTRACTN						
Means						
Term	*Fitted Mean*	*SE Mean*				
LoA						
4	175.00	2.89				
5	430.00	2.89				
6	430.00	2.89				
P. Stage						
CL	416.67	2.36				
EXTRACTN	273.33	2.36				

From analysis of variables in Table *4-21*, the effects of LoA and the process stage were assessed. The commonly chosen α-level of 0.05 was chosen and the results indicate the following: The p-value for both the LoA and P. Stage factor given as 0.000 and 0.001 are less than 0.05. Since these are less than the chosen α-level of 0.05, it means the effect of LoA and P. Stage on the rate of production is significant. This implies that, the mean rate of production is different for the different LoA and P. Stages. From the model summary, R^2 is 99.97%, and adjusted R^2

equals 99.93% which indicates that the model explains 99.97% of the variation in production rate when you use it for prediction. This is good for comparing different rate of production models since R is maximum.

From the coefficients, both LoA and P.Stage is significant at all levels (p= 0.000 or 0.001) since they are all less than α =0.05. Consequently, the effect of one predictor does not depend on the value of the other predictor. Also, The VIFs are all less than 5, which indicates that the predictors are not highly correlated. From the regression equation, employing Conventional automation (LoA = 4) in the 2 process stages applicable gives a mean rate of production of (345.00 - 170.00 LoA_4 + 71.67 P. Stage_CL - 71.67 P. Stage_EXTRACTN) 175 T/h, while SCADA (LoA = 5) and DCS (LoA = 6) results to a mean of 430 T/h each. This is evidence that SCADA (LoA = 5) and DCS (LoA = 6) are efficient in enhancing an increase in the sugar juice extraction and consequently the overall rate of production.

For relationship analysis, let:

> H_o: There is no linear relationship between LoA and rate of production (All the population means for the various treatments are equal)
>
> H_1: There exist a functional relationship between LoA and rate of production. True if $F_{cal} > F_{crit}$.

Since for LoA, F_{cal} (2601) > F_{crit}, (6.94), H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between LoA and power consumption. Similarly for P. Stage, F_{cal} (1849) > F_{crit}, (6.94), thus H_o is rejected and it is concluded that at 95% confidence level, there is sufficient evidence that there exist a relationship between P.stage and power consumption.

From Figure 4-36, the residuals of the production rate appear to follow a straight line. No evidence of non-normality, skewness, outliers, or unidentified variables exists. Hence, adequate to describe the correlation of level of automation with the rate of production.

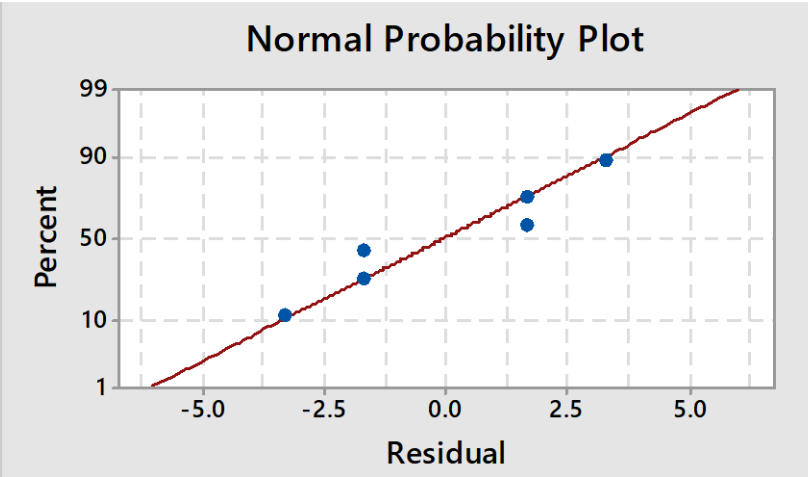

Figure 4-36 Residual Plots for Rate of production (T/h) (Source: Researcher, 2019)

Discussion

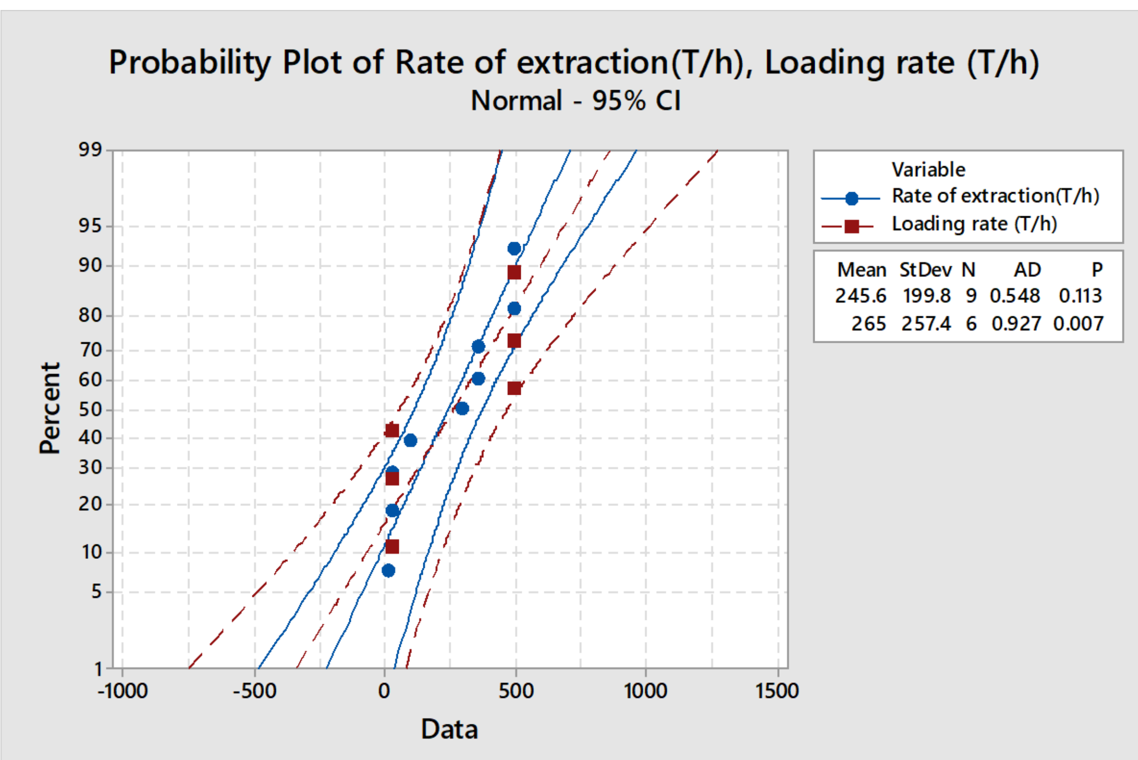

Figure 4-37 Probability plot of rate of extraction and loading rate (Source: Researcher, 2019)

Continuous improvement in the sugar processing is realized when there is an increase in the rate of extraction of quality juice, which subsequently increases the rate of quality sugar production. From Figure *4-37*, the rate of production conducted at three LoA indicates that level 4 has a low production rate of 100 T/h compared to levels 5 and 6 which depicted a rate of 360 T/h.

Continuous improvement is simply the improvement of the customer's value through improved product quality, increased production. This can only be achieved through implementation of reducing waste and employing strategies like lean manufacturing which will enable efficient use of resources. Another approach can be advanced manufacturing techniques that will enable real time and adaptive control of parameters to have faster productions.

Thus, a diffuser and six sigma mill tendon will enhance an improved rate of production than the conventional semi-automated mill tandems. This conforms to the findings of Oliverio (2013), where the juice extraction can reach only up to 80% with mill tandems, but can be higher when a diffuser incorporated with dewatering mills are used. In relation to lean automation, Six sigma emphasizes that the integration of lean and proper levels of automation will provide a suitable advanced control tool to best understand and identify parameters that affect or vary the process, and hence the overall performance of the organizations. Also, Ali et.al (2011) conforms to this finding through his study that to attain a continuous improvement, advanced manufacturing techniques like lean automation should be in place together with lean philosophy that will enable elimination of waste and efficient utilization of resources.

This concurs with the theory of constrains and waste reduction relying on two conceptual relationship of productivity, that is economistic concept which focuses on improving production efficiency by minimizing resource utilization (inputs) to attain goals (outputs) and the engineering concept which looks at the relationship between the actual and expected outputs (reduction of losses in the production lines). Therefore, a diffuser and six-sigma mill tandem incorporated with SCADA (LoA 5) or DCS (LoA 6) at all the process stages should be adopted if continuous improvement in sugar industries is to be realized.

Ultimately, the following mathematical model is proposed from the field data for adoption as an estimate for the optimum level of automation in improving the rate of production in sugar industries.

Rate of production (T/h) = 345.00 - 170.00 LoA_4 + 85.00 LoA_5 + 85.00 LoA_6 + 71.67 P. Stage_CL - 71.67 P. Stage_EXTRACTN

Therefore,

LoA 4 resulted to:

Cane loading rate = 345.00 – 170.00 + 71.67 = 246.67 say **250 T/hr**

Extraction rate = 345.00 – 170.00 – 71.67 = 103.33 say **100 T/hr**

LoA 5 and LoA 6 resulted to:

Cane loading rate = 345.00 + 85.00 + 71.67 = 501.67 say **500 T/hr**

Extraction rate = 345.00 + 85.00 – 71.67 = 358.33 say **360 T/hr**

4.6 Overall process performance index

According to Eq. 3-16, where

$$Process\ performance\ (y) = \left\{4\left(\frac{1}{y_1}\right) + 4\left(\frac{1}{y_2}\right) + \left(\frac{y_3}{4}\right) + \left(\frac{y_4}{4}\right)\right\} x100\%$$

The summarized overall sugar processing performance index was evaluated as shown

Table 4-22: Overall process performance parameter indices (Source: Researcher, 2019)

Parametersfor process	**Conventional automation LoA 4**	**SCADA LoA 5**	**DCS LoA 6**	
Adaptive control index, y_1	2.47	0.21	0.21	
Resource utilisation index, y_2	3311.2	2103.6	2101.2	
Quality production index, y_4	81.29	84.03	84.96	
Continous improvement index, y_3	175.00	430.00	430.00	
Process performance index	**65.69**	**147.56**	**147.79**	

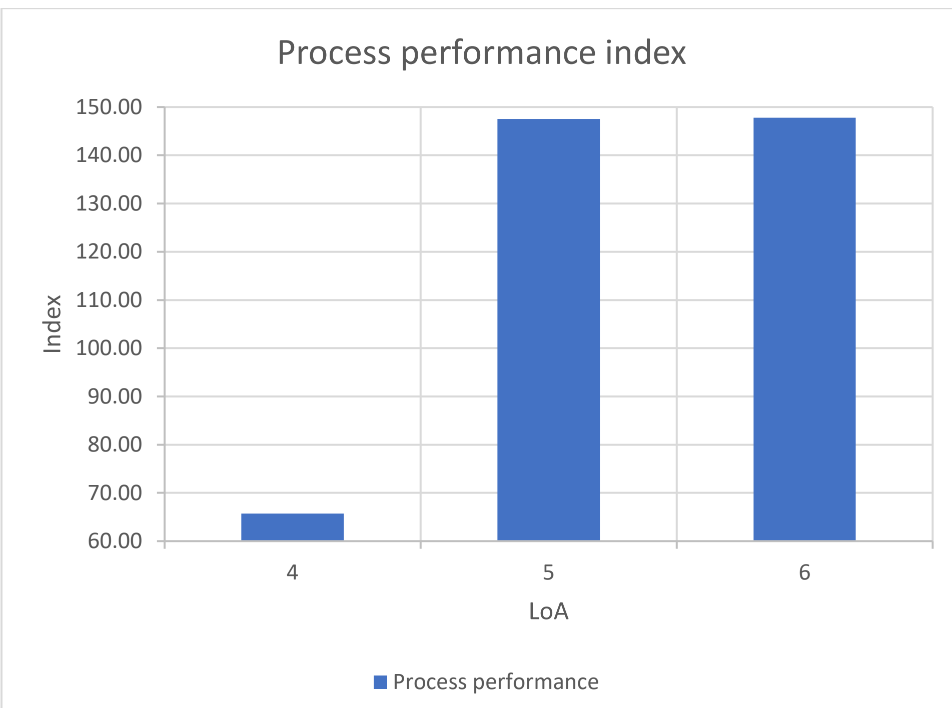

Figure 4-38: Process performance index (Source: Researcher, 2019)

The process performance of sugar industries was illustrated by four major indicators which influence the process parameters. From the summarized Table *4-22* of process parameter indices, it is observed that LoA 6 provides the most steadfast real time monitoring, control and maintenance of process parameters that will enhance quality production compared to LoA 5 and LoA 4. It allows negligible variability in the process parameters due to rapid response to changes. Also, when LoA 4 is employed, more resources are utilised as evidenced by high resource utilisation index. This is contrary to LoA 5 and 6 which have virtually negligible setups involved except when it is after a general plant overhaul. This is as a result of minimum variations in the process parameters due to their real time monitoring and control. Consequently, this will ultimately reduce both the lead times and power consumptions resulting in increased production with LoA 6 and 5.

Ultimately, from Figure *4-38* the process performance index for the three LoA indicates that LoA 6 has the highest performance, followed by LoA 5 then lastly LoA 4.Thus, sugar industries have a potential to adopt either SCADA (LoA 5) or DCS (LoA 6) if the process is to perform optimally for a sustainable and competitive sugar industry.

CHAPTER 5 : CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In relation to Adaptive control objective, the response time to an anomaly conducted in three stages showed that LoA 4 had a slow response to anomaly with the longest mean response time of 2.4-4.6 minutes compared to LoA 5 and 6 which depicted a rapid response to anomaly with the shortest response time of 0.5 min. Also, conventional automation (LoA 4) at the chopping (HD KNIV), shredding and juice extraction stages resulted to an average temperature variability of 2^oC, 3^oC and 4^oC respectively. While the SCADA (LoA 5) and DCS (LoA 6) showed no temperature variability in the three process stages. The lowest temperature variability in the conventional automation (LoA 4) was 1^oC recorded at HD KNIV (replicate 1) and the highest temperature variability being 5^oC at SHREDD (replicates 3) and EXTRACTN (replicate 1, 3, 4, and 5). It is evident that LoA 4 has the highest temperature variability in the three process stages while both LoA 5 and 6 recorded the lowest temperature variability. Thus LoA 5 and 6 provides set temperatures and pH to be easily monitored, controlled and maintained by the system... Thus, adopting levels 5 or 6, the process parameters will be controlled and maintained at the optimum levels. Therefore, levels 5 or 6 of automation will provide a steadfast real time monitoring, control and maintenance of process parameters that will enhance quality production.

In relation to the improvement of sugar quality objective, a high quality sugar is characterized by a high preparation index (PI), high sugar concentration in the juice (%brix) and (%pol). In all the stages level 6 recorded the highest PI and Brix values of 94% and 18%, and the lowest moisture in the bagasse of 40% at HD KNV and Extraction stages, compared to level 4 with

PI and Brix values of 77% and 17.3% at Shredder and Extraction stages respectively and a moisture content of 50%. This is because in level 6, the process parameters desired to optimize the process, are well monitored and regulated by the real time sensors. Also, the diffusion extraction that is usually fully automated provides an optimum means of extracting all the sucrose from the fibers compared to the mill tendons that are mainly monitored remotely. The diffuser has sensors and actuators that detects a variation in the process parameter and initiate appropriate corrective measure to maintain the optimum values. Level 6 involved the use of these sensing devices, visual and audio devices for communication. Thus adopting levels 5 or 6 the product, the apparent quality of the juice extract will be high, and consequently quality will be achieved and this will provide competitiveness in the sugar industry. This is due to negligible variability in the set process parameters when using LoA 5 or 6, as the response to changes is rapid compared to when LoA 4 is employed. It is therefore observed that the purity is directly proportional to the polarization and inversely proportional to the brix.

In the third objective, the rate of power consumption of the entire juice extraction process line when employing conventional automation (LoA 4) was relatively higher with a total of 45044 kW compared to when SCADA (LoA 5) or DCS (LoA 6) are used with a total power consumption of 42058 kW and 42008 kW respectively. Therefore, using LoA 5 or 6, the overall power consumption was lower than the conventional milling technologies. This is attributed to the characteristics of the LoA 5 and 6, where speed variable electro mechanical and hydraulic drives are employed in form of efficient shredders and high density knives compared to the conventional drives used in LoA 4 turbines. Also, LoA 5 and 6 uses a diffuser in the extraction which is exclusively automated with frequency variable drives thus consuming less power while producing quality sugar with adaptive control on parameters. This is contrary to when LoA 4 is employed where mill tandems are withdrawing relatively high power to operate at the expense of low quality and production rate. It can be seen that LoA 5 and 6 have virtually negligible setup involved except when it is after a general plant overhaul. This is as a result of minimum variations in the process parameters due to their real time monitoring and control.

Lastly, continuous improvement is simply the improvement of the customer's value through improved product quality and increased production. This can only be achieved through implementation of reducing waste and employing strategies like lean manufacturing which will enable efficient use of resources. Another approach can be advanced manufacturing techniques that will enable real time and adaptive control of parameters to have faster productions. The rate of production at level 4 was 100 T/h which was low compared to levels 5 and 6 at a rate of 360 T/h. This conforms to the findings of Oliverio (2013), where the juice extraction can reach only up to 80% with mill tandems, but can be higher when a diffuser incorporated with dewatering mills are used. Therefore, levels 5 or 6 of automation utilizes the efficient shredders that consume less power compared to level 4 that uses high torque knives. Hence, more power required with conventional level of automation. Consequently, this will ultimately increase both the lead and set up times resulting in reduced production in LoA 4. Thus, sugar industries have a potential to adopt either SCADA (LoA 5) or DCS (LoA 6).

The process performance index for the three LoA indicates that LoA 6 has the highest performance, followed by LoA 5 then lastly LoA 4.Thus, sugar industries have a potential to adopt either SCADA (LoA 5) or DCS (LoA 6) if the process is to perform optimally for a sustainable and competitive sugar industry.

5.2 Recommendations

- In summary, lean (Six-sigma) automation which consists of LoA 5 (SCADA) or LoA 6 (DCS) according to Garcia (2015), provides the optimum lean automation that local sugar industries require to have a sustainable and competitive process performance. Therefore, it should be considered for adoption and implementation within the sugar processing line as the appropriate advanced manufacturing technique that will enable real time monitoring of process variables, minimization of resource wastages, quality production and continuous improvement in the sugar industry.
- An investor interested in lean automation technology may want to know its cost implications. However, this study did not address the aspect of its cost. Hence, further investigation into the cost of adopting lean automation (LoA 5 and 6) in sugar industry should be conducted and cost-benefit analysis evaluated.
- The study was limited to two dimensions of automation namely adaptive control and material handling. It is advised that the other dimensions of automation be studied in relation to its adoption in sugar industry to check if process efficiency can be increased. These includes: numerical control, robotics, assembly and flexible fixturing.
- Apart from the technological inadequacies prevailing, other factors that hinder the sustainability of sugar industries need to be investigated and appropriate remedies recommended. These factors were assumed constant during this study. Among them includes: political influence, decrease in investment portfolio, poor agricultural practices and increase in credit and competition costs from imports.

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APPENDIX

Appendix A: A summary of the tabulated results

Table A: A summary of the tabulated results for various parameters.

P. Stage	LoA	total power (Kw/day)	Response time (min)	cycle time (min)	set up time (min)	Loading rate (T/h)	Purity (%)	Process temp Var (0C)	PI (%)	Brix in juice (%)	Process pH	Pol (%)	Rate of extraction(T/h)
WB	4	576.0	2.4	5.2	2.6								
WB	5	216.0	0.6	3.1	0.6								
WB	6	216.0	0.6	3.1	0.6								
CL	4	2880.0	4.6	7.7	5.3	500.0							250.0
CL	5	1680.0	0.5	4.9	0.5	500.0							500.0
CL	6	1680.0	0.5	4.6	0.5	500.0							500.0
FT	4	3168.0	3.0			30.0							250.0
FT	5	720.0	0.5			30.0							500.0
FT	6	720.0	0.5			30.0							500.0
KNIV	4	10080.0		5.0			81.1	2.0	65.0	12.5		10.1	
KNIV	5	10080.0		1.0			83.0	0.0	69.0	13.6		11.3	
KNIV	6	10080.0		1.0			83.0	0.0	70.0	13.6		11.3	
MC	4	1080.0										0.0	
MC	5	720.0										0.0	
MC	6	720.0										0.0	
SHREDD	4	21600.0		5.0			83.5	3.0	77.0	13.4		11.2	
SHREDD	5	10080.0		1.0			85.2	0.0	81.0	14.5		12.4	
SHREDD	6	10080.0		1.0			85.2	0.0	85.0	14.5		12.4	
HD KNV	4			5.0			84.5	2.0	89.0	15.1		12.8	
HD KNV	5	18112.0		1.0			87.4	0.0	92.0	16.3		14.2	
HD KNV	6	18112.0		1.0			87.4	0.0	94.0	16.3		14.2	
EXTRACTN	4	5660.0		4.4			86.5	4.0		17.3	7.0	15.0	100.0
EXTRACTN	5	450.0		7.4			89.5	0.0		18.0	6.5	16.1	360.0
EXTRACTN	6	400.0		7.4			89.5	0.0		18.0	6.5	16.1	360.0

Appendix B: Bagasse from LoA 4 Mill tandems and level 6 diffuser

Figure B: Bagasse from LoA4 Mill tandems (PI is low and Moisture content High (Source: Researcher, 2019)

Figure C: Bagasse from level 6 diffuser (PI is high and Moisture content low (Source: Researcher, 2019)

Appendix C: Experimental setups for LoA 4, LoA 5 and LoA 6

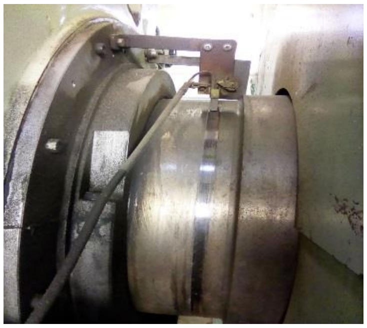


Figure C-1: Level 4- Control circuits

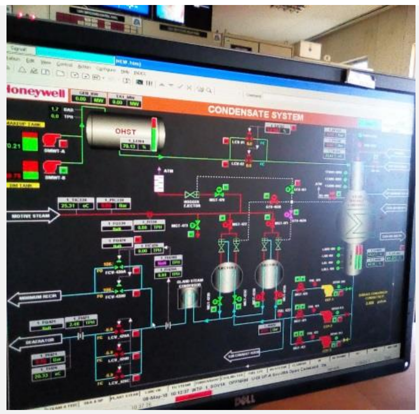
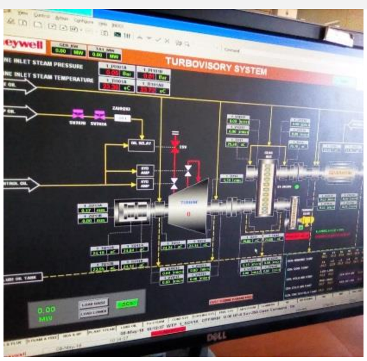
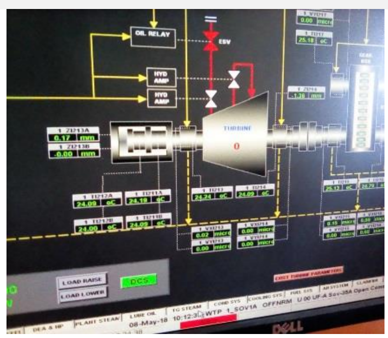


Figure C-2: Level 5-SCADA





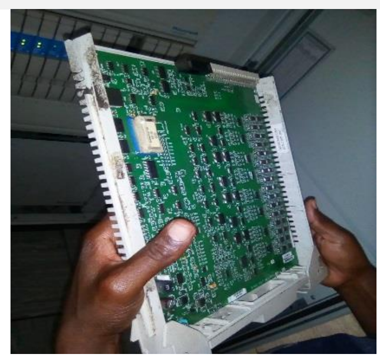


Figure C-3: Level 6-DCs