MAE 526

FUNDAMENTALS OF PRODUCT DESIGN

MINI PROJECT 1

By Yash Chaturvedi

Introduction

This first mini-project focuses on the relationship between market opportunities, customer needs identification, and solution-neutral concept generation. I have identified a customer who has a problem which can be solved using new product introduction.

Task 1: Developing a problem statement for the customer

For my project here, I interviewed my roommate and friend, **Arjun Madhusudan** who is a computer science graduate student at North Carolina State University majoring in Game Development and I am developing a work desk which is adjustable and has a built – in refrigerator along with some extra features. His problem is, as a gamer and a computer scientist he spends most of his time on a table, so he needs a setup or working area where fresh food and drinks are easily accessible when he does not have sufficient time to go into kitchen also when sometimes sitting for longer periods gets tiring he has to stand up and work.

Solving this problem is important because, as per gamers, user interface of the game, peripherals and setup significantly impacts their performance in a game. Competitive gaming is a focussed sedentary activity and at times the gamer cannot even pause games to have drinks or food and while sitting for long periods a standing break is required for blood circulation in the lower body. Hence, the requirement of this product focusses on a table which can be adjusted according to the user's desire and an accessible refrigerator to keep fresh foods and drinks.

Currently, he must wait for a game match to get over and then get into kitchen to eat or drink and while working for long period he must stop working and lie down to relax. The only option available for him right now is to buy a table whose height can be adjusted and a separate mini refrigerator.

In the market this time there is no such product available which can do both cooling and height adjustment but there two separate concepts available which can fulfil these needs individually. One is Xdesk Air for height adjustment table/desk and other is a coffee table with a cooler drawer.

Task 2: Customer interview and identification of customer attributes/needs

After interviewing the customer, I was able to identify the following customer needs:

- Easy movement of the table
- Cools food items
- Adjustable Height
- Aesthetically Appealing
- Easy cable management
- Durable
- Ample Space on the top

In context of Kano Model, these customer needs can be classified into Basic Needs, Delight needs and Surprise needs.

Basic	**Delight**	**Surprise**
Ample Space on the top	Easy movement of table	Easy cable management
Durable	Cools food items	
Aesthetically Appealing	Adjustable height	

Basic needs are the needs which the consumer assumes are satisfied with the product description. Here in this case, the customer automatically assumes that the table will have ample space on the top and it will last long with great aesthetic appeal.

For delight needs are explicitly stated here they will be that the built-in refrigerator cools the food items and the table has some sort of adjustable mechanism (mechanical or electromechanical) with its easy movement.

Considering surprise needs the customer satisfaction goes up exponentially. Here ease of managing cables and if they are inconspicuous would be surprising.

After brainstorming and carefully thinking over and over about the needs that are not addressed, or the latent needs are:

The customer during the interview never addressed about

- footrest

- Boot Space beneath the table
- Sturdiness

Affinity Diagram

The needs with closest affinity are listed in the same column

Ample space on the top	Cools food items	Aesthetics	Ease of Movement	Cable Management	Adjustable height
Boot space		Lasts long			
Footrest		Sturdiness			

Currently in the market the products mentioned above can fulfil every need except the cable management and presence of shelves. The Xdesk Air can fulfil height adjustment, ample tabletop space, boot space while the coffee table has a built-in refrigerator but no height adjustment or the features the former has.

Cable management and Shelves are currently not met but also, we cannot find a table in the market which can address all the needs.

My new design solution will address all the needs including cable management, shelves, adjustable height and built-in refrigerator.

Task 3: Identification of technical attributes and relationship with CAs

Technical Attributes for the product:

**The larger or the smaller the value is the customer's preference

- **Length:** Larger is preferred
- **Width:** minimum is preferred
- **Weight:** Lesser the better
- **Height Range:** Not too large not too small
- **Cooling capacity:** High is preferred
- **Refrigerator Capacity:** High is preferred (Volume of the refrigerator)
- **Power input:** Low is preferred (can be referred to as electric power or human power)
- **Material:** High Quality is preferred
- **Strength:** High is preferred
- **Service Life:** Larger lifetime is preferred

House of Quality

Customer Attributes	Technical Attributes: Length	width	height range	Weight	cooling capacity	refrigerator capacity	power input	material	strength	service life
Ample space on the top	s	s		w					w	
Easy movement of the table	m	m	m	s						
Adjustable Height			s				s			
Cools Food Items					s	s	s			
Aesthetically Appealing								s		m
Easy Cable Management	m	m	m							
Durable	m	m						s	s	s
Boot Space	s	s	s			s				
Sturdiness	s		s					s	s	s
Footrest		m								

s= strong relationship

m = moderate relationship

w = weak relationship

Relationships between Customer and Technical Attributes:

- **Ample Space on top:** Ample Space is strongly related to the length and width of the top as it would be directly proportional to them. As the space increases the weight might increase as amount of material increases. Also, the space will loosely be related to strength, as this situation can be analogous to a beam with poles far apart.
- **Easy movement of table:** This depends on all length, width, height range and strongly with the weight of the table.
- **Cools food items:** The cooling capacity, the volume or capacity of the refrigerator and power input is strongly related to the heat extraction.
- **Adjustable Height:** The tabletop can be adjusted to any height between the maximum and the minimum height. Also, the height adjustment is strongly related to the power of the motor driving the table top.

- **Aesthetic Appeal:** Materials strongly influence the aesthetic appeal of the product and sometimes loss of aesthetic appeals leads to discarding of a product.
- **Durable:** The durability of is strongly related to material, strength and service life and moderately related to the dimensions.
- **Easy Cable Management:** Cables can be easy managed when we have space.
- **Boot Space:** Directly related to dimensions of the table and refrigerator capacity as larger the refrigerator capacity lesser the boot space.
- **Sturdiness:** Depends on length (longer is preferred), height and materials.
- **Footrest:** Will be placed according to the width of the table.

Correlation Matrix for Technical Attributes

	Length	width	height range	Weight	cooling capacity	refrigerator capacity	power input	material	strength	service life
Length	+			+		+			-	
width		+		+		+			-	
height range			+	+			+		-	
Weight	+	+	+	+	+	+			+	
cooling capacity				+	+	+	+			
refrigerator capacity	+	+		+	+	+	+			
power input			+	+	+	+	+			
material				+				+	+	+
strength	-	-	-	+				+	+	
service life								+		+

+	Positive Correlation
-	Negative Correlation

Correlation matrix for technical attributes:

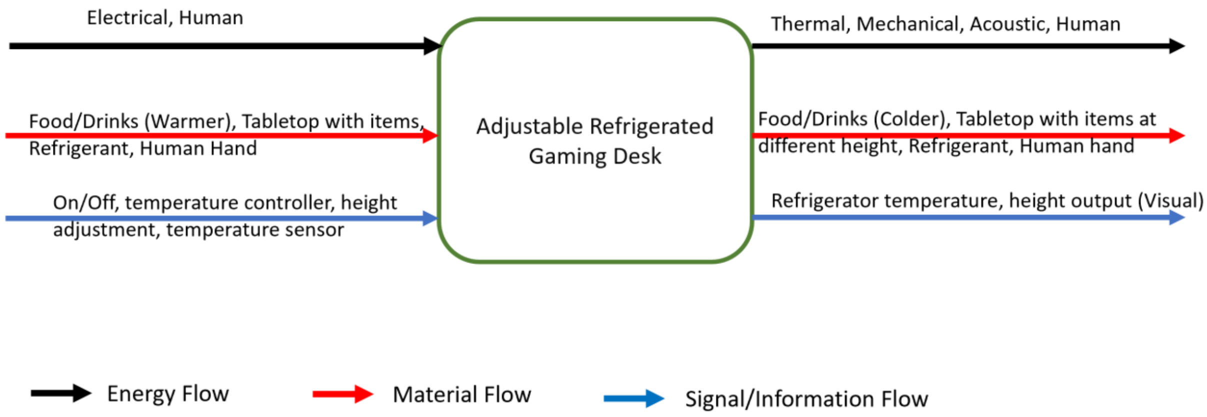
- **Length:** Has a positive correlation with weight and refrigerator capacity while is negatively correlated to strength.
- **Width:** positive correlation with weight and refrigerator capacity; negative correlation with strength.

- **Height Range:** positively correlated with weight and power input and negatively correlated with strength.
- **Weight:** Is positively correlated with all the technical attributes except service life.
- **Cooling capacity:** is positively correlated to weight, refrigerator capacity and power input.
- **Refrigerator Capacity:** is positively correlated to length, width weight, cooling capacity and power input.
- **Power Input:** Positive correlation with height range, cooling capacity and refrigerator capacity.
- **Material:** holds positive correlation with strength and service life.
- **Strength:** positive correlation with weight and material but a negative correlation with length, width and height range.
- **Service life:** Positively related with material.

I cannot find a product in the market which performs the similar function. Though there are two separate products that are similar in functions but there exists not single product which can do both. Hence, benchmarking in this case cannot be done.

Task 4: Functional Diagram Construction

Upper Level Black Box

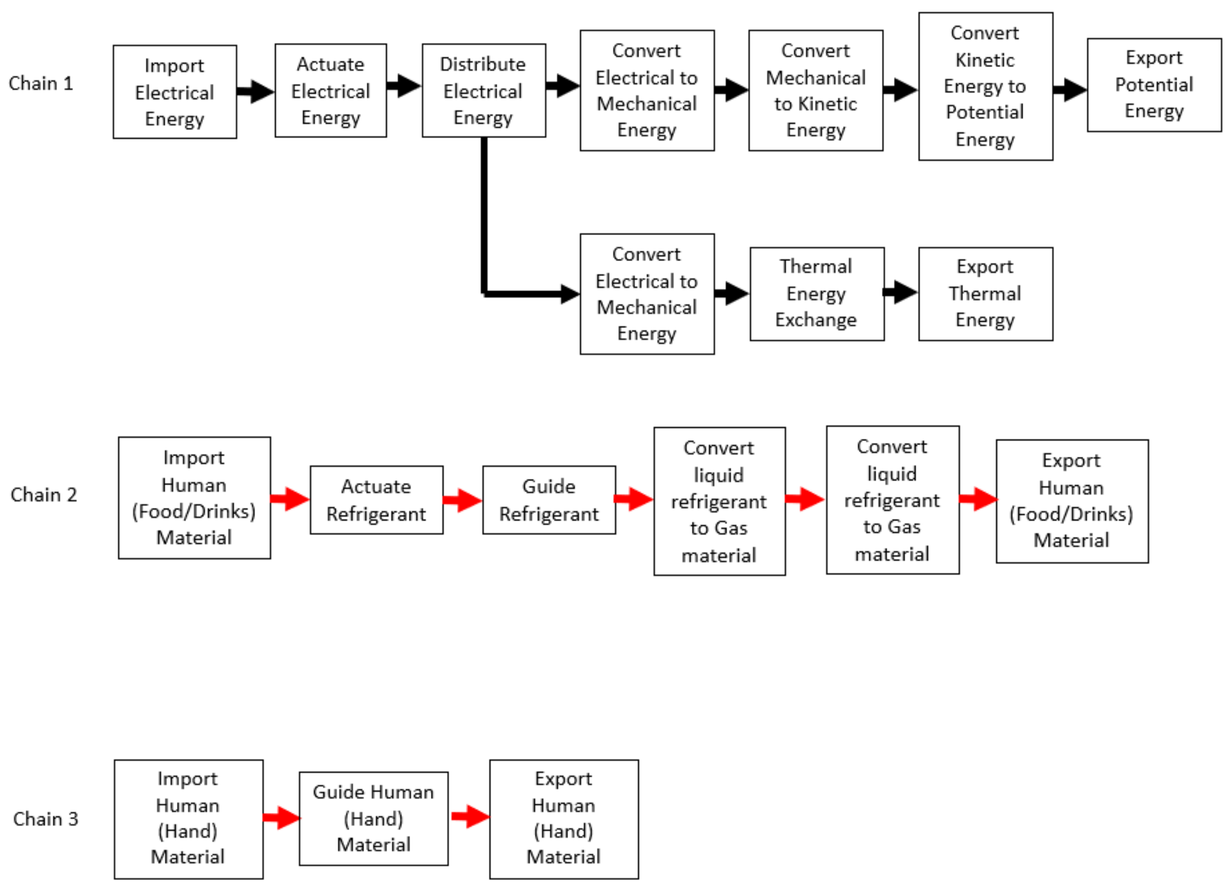


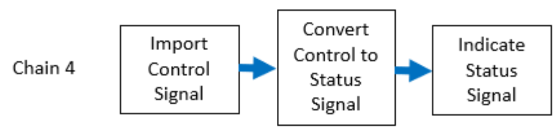
List of Function Flow pairs

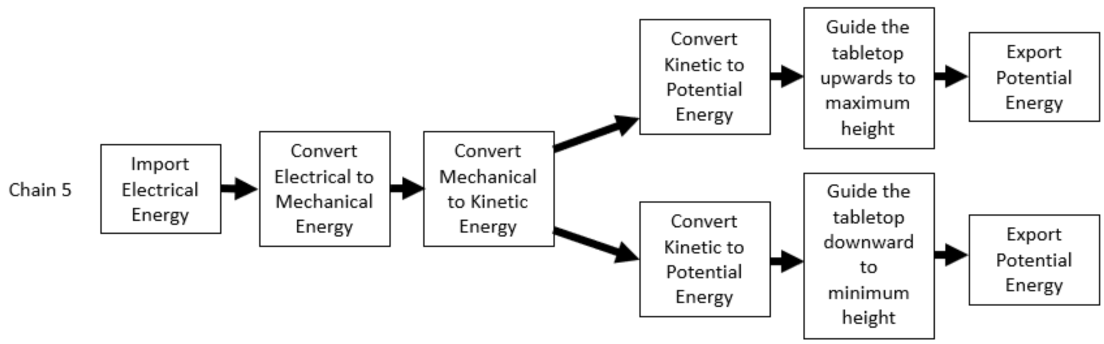
- Import Electrical Energy
- Actuate Electrical Energy
- Convert Electrical to Mechanical Energy
- Convert Mechanical to Kinetic Energy
- Convert Kinetic Energy to Potential Energy
- Thermal Energy Exchange
- Actuate refrigerant
- Convert liquid refrigerant to gas material
- Convert gas refrigerant to liquid
- Guide Refrigerant
- Distribute electrical energy
- Guide the tabletop upwards up to maximum height
- Guide the tabletop downwards up to minimum height
- Import control signal
- Import Human (Hand) Material
- Guide Human (hand) material
- Import thermal energy
- Import Human (Food/Drinks) Material

- Export Human (Food/Drinks) Material
- Convert Control Signal to Status Signal
- Convert Mechanical Energy to Acoustic Energy
- Export Potential Energy
- Export thermal energy
- Import control signal
- Indicate Status Signal

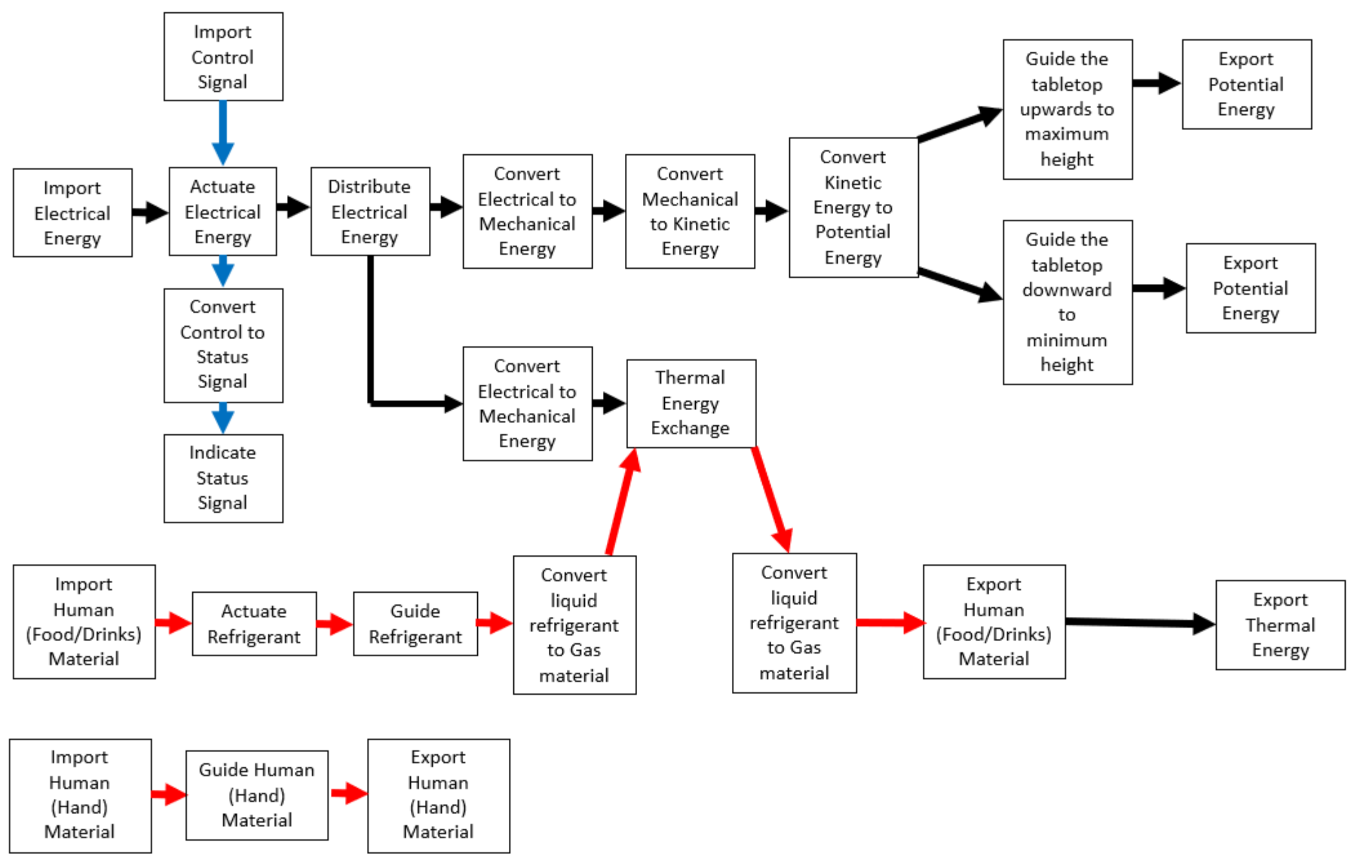
Generating Function Chains







Aggregating Function Chains by Connecting Flows



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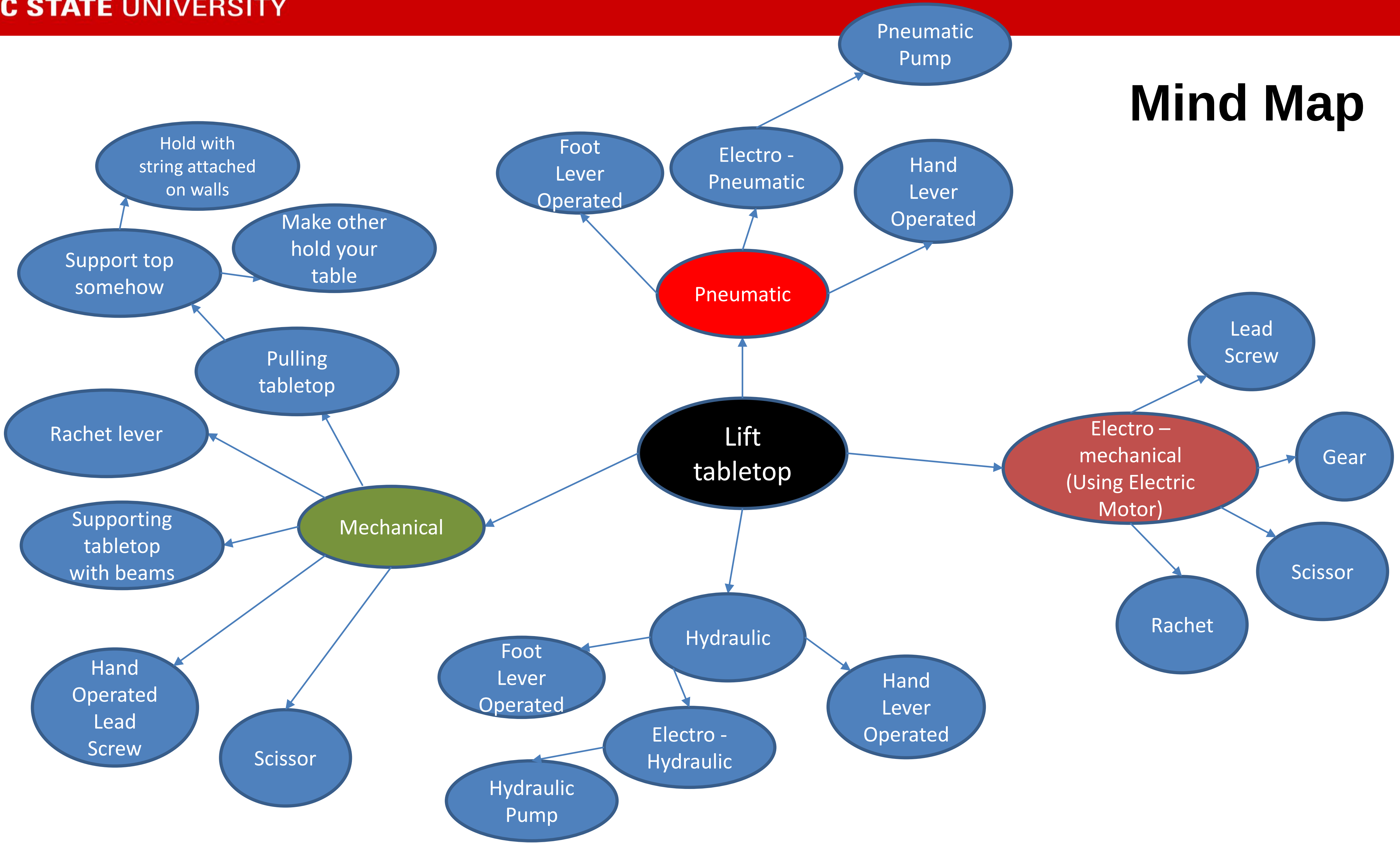
Fundamentals of Product Design
Mini Project 2 – Refrigerated Adjustable Work Desk

by Yash Chaturvedi

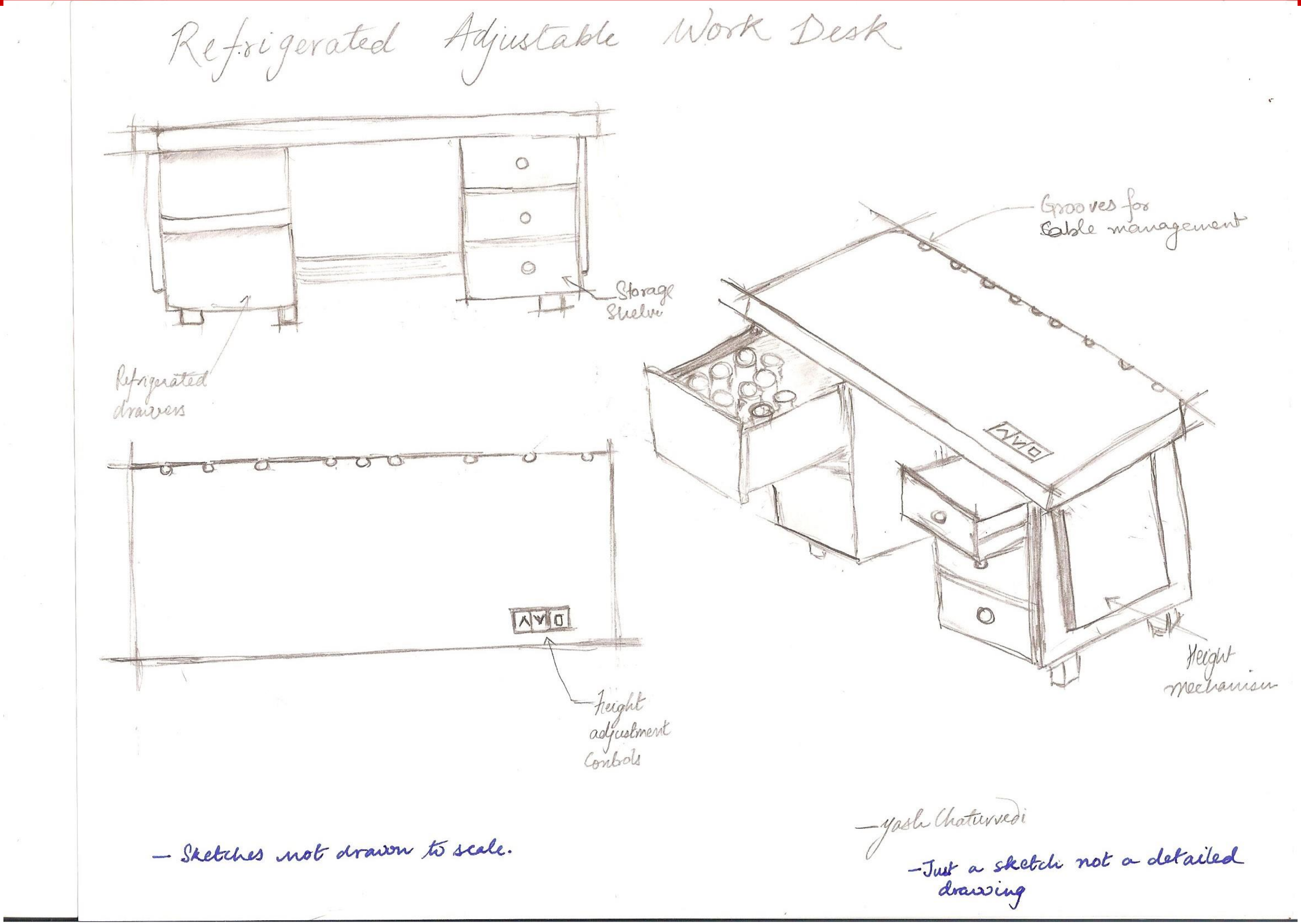
Refrigerator Adjustable Work Desk

- Desk made specifically for gamers and people who spend most of their time at desk
- Has a built-in refrigerator
- The tabletop can be adjusted at any height

Mind Map


Lift tabletop
Pneumatic
Foot Lever Operated
Electro - Pneumatic
Pneumatic Pump
Hand Lever Operated
Electro – mechanical (Using Electric Motor)
Lead Screw
Gear
Scissor
Rachet
Hydraulic
Foot Lever Operated
Electro - Hydraulic
Hydraulic Pump
Hand Lever Operated
Mechanical
Pulling tabletop
Support top somehow
Hold with string attached on walls
Make other hold your table
Rachet lever
Supporting tabletop with beams
Hand Operated Lead Screw
Scissor

Sketch


Refrigerated Adjustable Work Desk
Grooves for Cable management
Storage Shelve
Refrigerated drawers
Height adjustment Controls
Height mechanism
-Yash Chaturvedi
- Sketches not drawn to scale.
-Just a sketch not a detailed drawing

System Design Variables

- Refrigeration Capacity
- Refrigerant Type
- Structural Strength
- Height Adjustment Mechanism
- Power of the actuator
- Wiring

System Attributes (All)

- Height Adjusting Speed
- Width
- Length
- Volume of the refrigerator
- Cooling Rate
- Surface Finish
- Service Life
- Power input
- Strength
- Service Life
- Material
- Load Capacity
- Height Range

Systems Attributes (4)

- Height Adjusting Speed
- Volume of the refrigerator
- Material
- Load Capacity

Benchmarking

Attribute	My product	Kings Bottle mini fridge	3000 Ergonomic Gaming Computer Desk	Xdesk Pro
Height Range	26”-50”	Not Adjustable	33.5”-49.5”	24”-51”
Volume of the refrigerator	47 liters	52 liters	Not Applicable	Not Applicable
Rated Electric Power Input	300 W	76 W	0 W (Manual Adjustment)	200 W
Load Capacity	750 lbs	Not Applicable	200 lbs	630 lbs

Defining 3 attribute levels

Height Range	Volume of the refrigerator	Rated Electric Power Input	Load Capacity
16”	47”	76 W	200 lbs
24”	52”	200 W	630 lbs
25”	60”	300 W	750 lbs

One system attribute with mathematical relationship

The load capacity (a) will depend on dimensions (x = length, width) and their relationship can be explained by the following

- Load Capacity can be calculated by the following equation:

$$\sigma = \frac{M * y}{I}$$

Where, σ is the stress on the tabletop
M is the Maximum moment
y = Distance of the applied moment from the neutral axis
I = Cross – Section Moment of Area

Another system attribute with mathematical relationship

Rated Power input (a) will depend on the power rating of each individual electrical equipment (x) in the system. This can be described by:

$$Net\ Rated\ Power = \sum Power\ Rating\ of\ electrical\ equipment$$

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Mini Project 3 – Refrigerated Adjustable Work Desk

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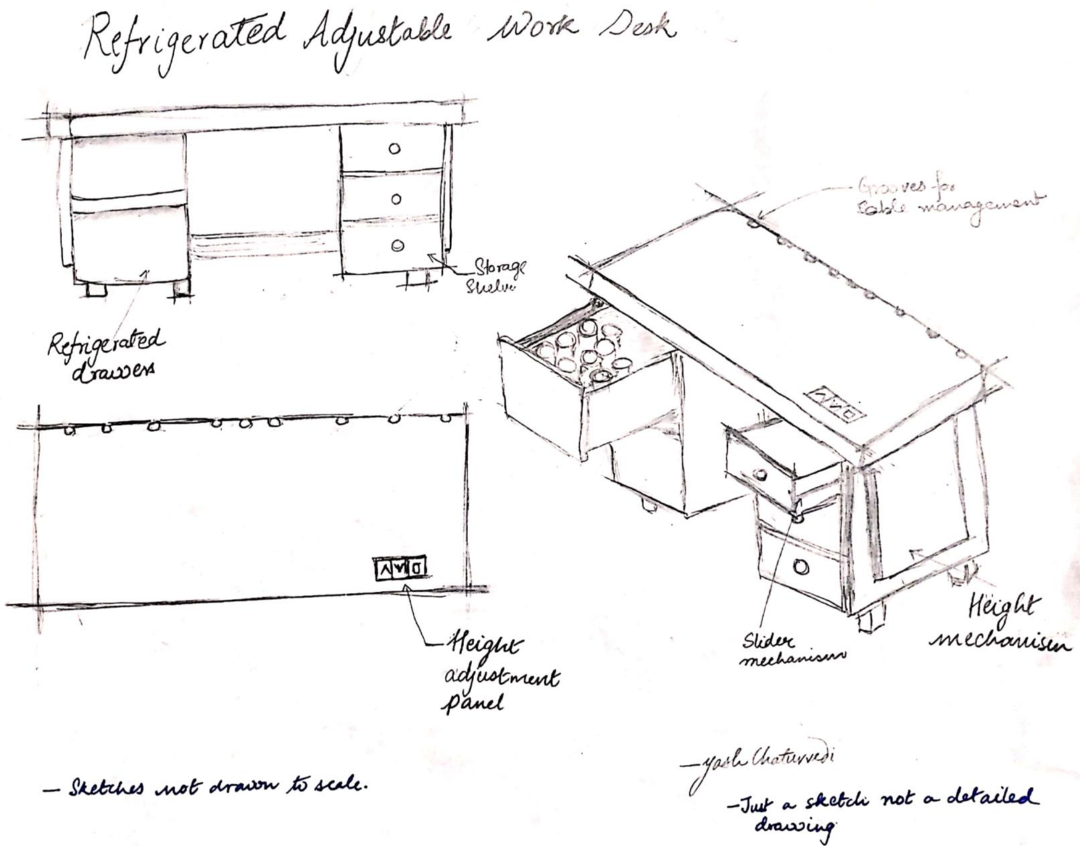
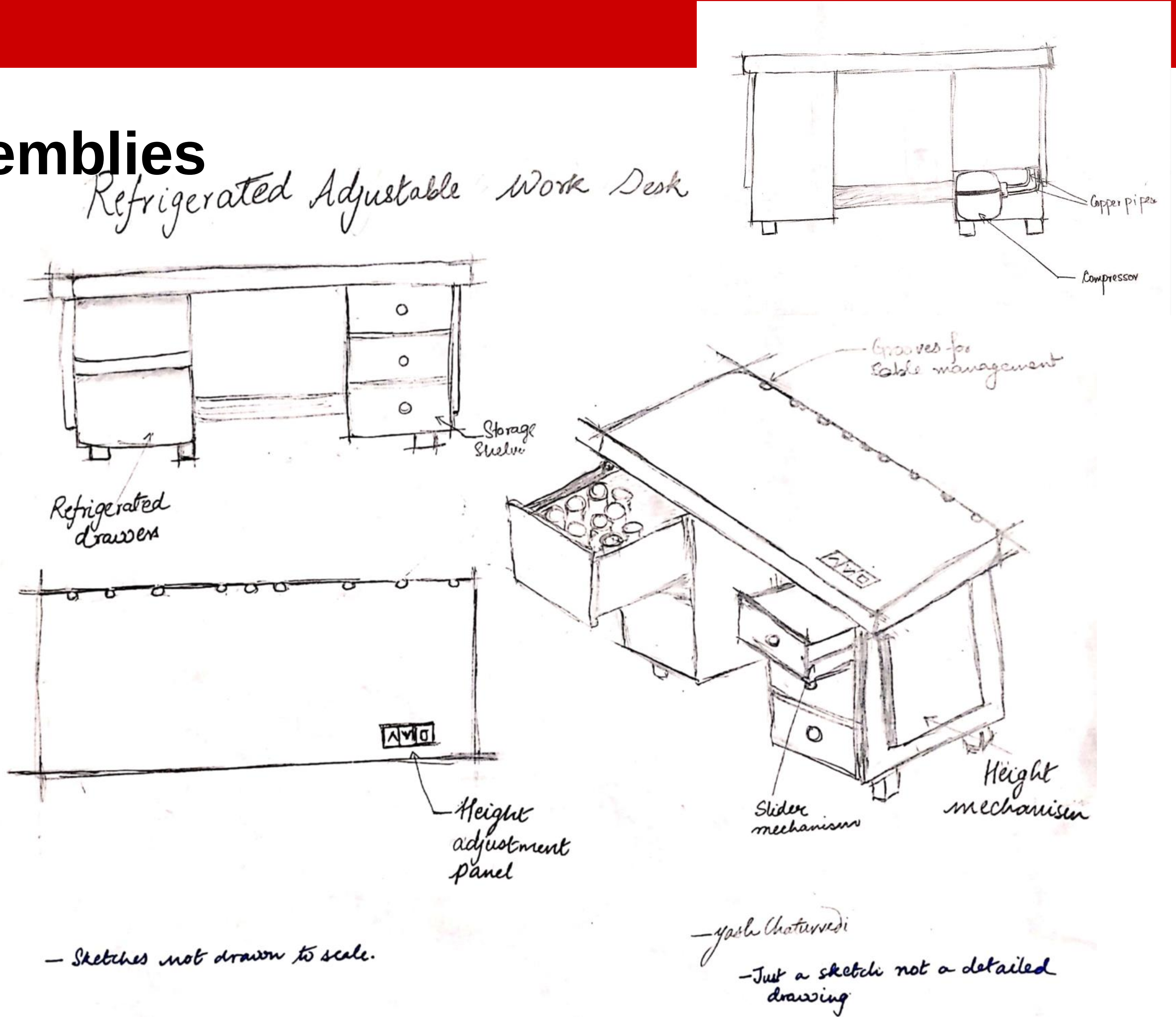
Refrigerator Adjustable Work Desk

- Desk made specifically for gamers and people who spend most of their time at desk
- Has a built-in refrigerator
- The tabletop can be adjusted at any height



Major components/assemblies

- Linear Actuator
- Compressor
- Copper Pipes
- Coolant
- Circuit board
- Aluminum frame
- Tabletop
- Glass Interactable panel
- Sliders
- Cabling
- Insulation



Component/Assembly

Comp/assembly	weight	material	Manufacturing Process	Assumptions
Linear Actuator	3.72kg	Aluminum	Assembly + Casting	Contains small parts
Compressor	5.5 kg	Aluminum	Assembly + Casting	Contains small parts into an assembly
Heat Pipes	1.82 kg	Copper	Pipe Drawing	
Coolant	0.68 kg	R134A	Scott Process	Named after inventors
Circuit Boards	0.1 kg	Fiber Glass	Lithography	
Table Frame and Drawers	50 kg	Aluminum	Extrusion and joining	
Tabletop and drawers	7.2 kg	Wood	Gluing	Assuming a wooden board
Panel	0.09 kg	Glass	Molding	
Cabling	1.8 kg	Copper + PVC	Drawing	Copper wires with PVC Coating out of which 1kg is copper and rest PVC
Sliders	4 kg	Aluminum	cast	
Insulation	2.5 kg	Polyurethane foam	molding	

Production phase

Material/Process	Amount	Indicator (per unit amount)	Result
Aluminum	63.22 kg	780	49,311.6
Copper	2.82 kg	1400	3948
Wood	7.2 kg	39	280.8
Glass	0.19 kg	58	11.02
PVC	0.8 kg	240	192
R134a	0.68 kg	150	102
Polyurethane	2.5 kg	420	1050
Extrusion of Aluminum	63.22 kg	72	4551.84
Drilling of Aluminum	0.7 kg	800	560
Copper Extrusion	2.82 kg	72	203.4
Molding of Polyurethane	2.5 kg	12	30
Total (mPt)			48,941.94

Assumptions:
Bending of copper pipes neglected
Copper pipe has same extrusion indicator as Aluminum
Processing of wood board is not provided in Eco 99 Manual

The table presents production and processing of elementary materials used in the product.
Aluminum being the major component, whole table frame integrated with refrigerator box and the sliders are made up of extruded aluminum.

Copper pipes are used as heat exchangers and wood as tabletop and drawers will glass touch panel for movement of top.

R134a used as refrigerant has an indicator value of 150 mPt.

Use Phase

The product will be in continuous use starting from all the items (not consumables) kept on the tabletop.

The refrigerator is meant to work for at least 5 years of continuous running with little or no maintenance.

The tabletop is moved for at least 2 times per day (2 times comprises of two cycles from the sitting height of the user to the standing height and back to seating height).

The only consumable is electricity. Food items for refrigerator will not be considered as consumables.

Use Phase

Material/Process	Amount	Indicator (per unit amount)	Result
Electricity Low voltage	370 kWh/year	26	9,620 mPt

Assumptions
Indicator rating of Europe Low Voltage is used

Net consumption of electricity in an hour is approximately rated to be around 42.5 W (not to be confused with input power) yearly it will consume 370 kWh per year.

Disposal phase

Material/Process	Amount	Indicator (per unit amount)	Result
Aluminum	63.22 kg	-110	-6954.2
Copper	2.82 kg	-1328	-3744.96
Wood	7.2 kg	-36	-259.2
Glass	0.19 kg	1.4	0.266
PVC	0.8 kg	37	29.6
R134a	0.68 kg	7300	4964
Polyurethane	2.5 kg	2.8	7
Total (mPt)			-5987.094

Aluminum Indicator is for incineration of aluminum frame along with the Polyurethane integrated with the refrigerator.

Indicator rating of copper is given to be -1328 as production has a rating of 1400 mPt and the extrusion takes 72mPt. Hence, net rating of recycling copper can be assumed to be -1328 mPt.

Similarly, for wood the production rating for wooden board is 39 mPt and recycling all the wood while compensating for any processing can be assumed to be -36 mPt. Glass is disposed to landfill and PVC over the wires are incinerated to obtain copper.

Disposal of refrigerant have large affect on the environment thus its indicator value is 7300 mPt.

Engineering Change

There can be design change in the refrigerator where the drawers can be replaced by an Aluminum framed glass door. This will reduce the overall weight of the aluminum by approximately 4 kg thus reducing production rating by 3120 , Disposal rating by -440, Process Rating by 28 [illegible]

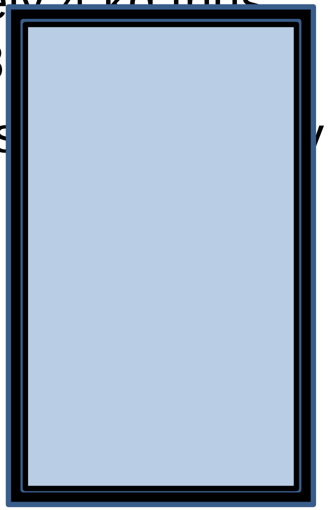
Increased glass weight by 1 kg for which production rating increased by 58 and dispos [illegible] 1.4.

Net change in Production phase from **48941.94** to **45591.94**

And net change in disposable phase from **-5987.094** to **-5548.494**

Thus final impact from the production phase has reduced

And impact from disposal phase has increased.



Second Engineering Modification

This modification is done after the first modification has been done

- Changing the storage drawers to a storage cabinet, thus reducing the material from both Aluminum and Wooden Side. Apparently, the weight reduction in Aluminum is approximately 2kg and in wood about 0.6 kg.

Net change in Production phase from **45591.94**

to **43864.54.**

And net change in disposable phase from **-5548.494.094** to

-5306.894.

Class topics

The two most useful topics that I found most valuable:

- Brainstorming and Innovation: We all think but thinking strategically is a different thing. We are never taught how to think strategically and structurally anywhere else. Although these thinking and brainstorming techniques is not limited to this course but can be applied anywhere and can come handy.
- Failure Mode Effect Analysis (FMEA): FMEA is an important tool in engineering to allow the engineer analyze any possible failures in a product and built measure on it. Though it is very subjective it can help get current knowledge of failures and make continuous improvements in the product.

THANK YOU

GRADUATE RESEARCH PROJECT REPORT

-by YASH CHATURVEDI

TECH in 2035

1. THE WORLD IN 2035

The simulation of the world made in "Global Trends 2030: Alternative world", by National Intelligence Council is beginning to take shape. Potential 'BLACK SWANS', that were supposed to disrupt the impact of events on which the simulations were made have already taken place [1]. Disruption in precipitation patterns in Asian Countries [2], Cyber Attacks such as 'Ransomware' and the Severe Pandemic involving easily transmissible novel respiratory pathogen that kills more than one percent of victims: COVID-19, have already occurred. So now we can envision an alternative reality which will be different from what was predicted eight years from now.

Still there is a probability that humans, with their innate capability to progress may actually accelerate the development to point which might resemble or very least similar to the 'stimulated future'.

Tectonic shifts across the world, like the widespread aging will lead to workforce shortages [Figure 1], high urbanization rates in Asian countries [Figure 2], shortage of food and natural resources etc. [1], will trigger the utilization of technological, economic and political reforms. It is eminent to adopt state of the art methods to compensate for all the changes. 2019 Annual report by Bill and Melinda Gates Foundation [3] report that by 2030 the youngest workforce will belong to African continent which at this moment is hurdled with health, education, economic and political issues. Believing what forecasts say it would be safe to assume that the world scenario will have an extremely different façade.

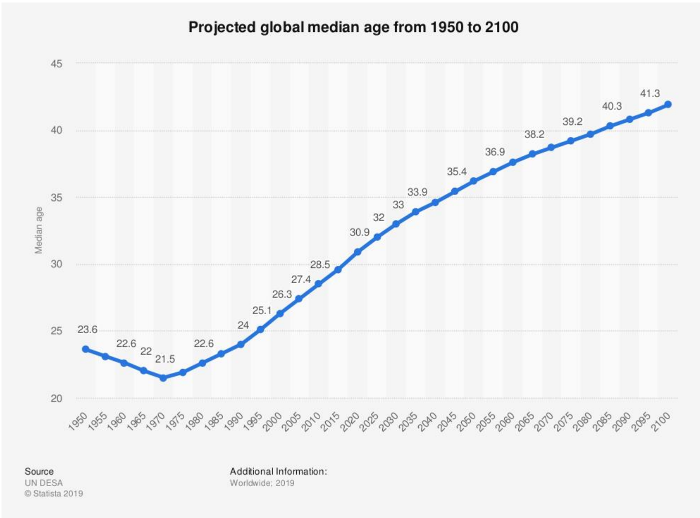


Figure 1: Global Median Age 1950-2100

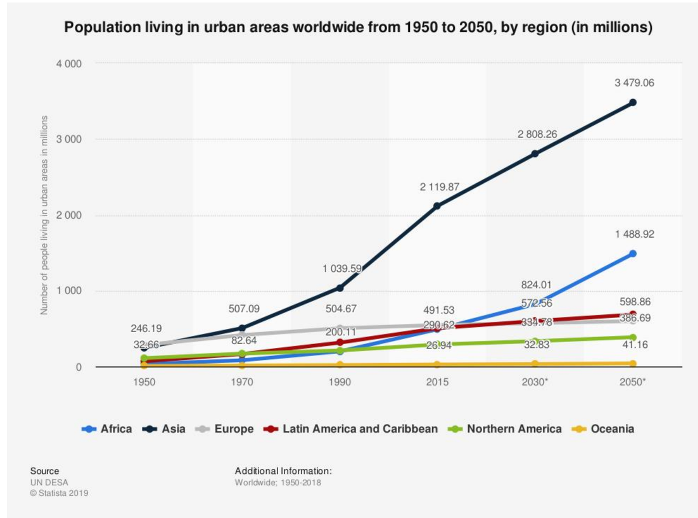


Figure 2: Change in urbanization by region 1950-2050

Interpreting data from historical trends, it can be observed that introduction of changes or tectonic shifts be it technological, economic, political, or geopolitical have been inspired by the major events of immediate past. For example, advancements in post-World War era. Taking into consideration the current health crisis, it will not be wrong to say that next decade and half would be accentuated as an era of health industry. Similarly, the

2. TECHNOLOGICAL SOLUTIONS WORTH INVESTING IN

The previous section established the fact that the next few years would be crucial for health industry, but this is just the tip of an iceberg, entailing are the technological solutions that would make this idea viable. With the regulations in the health industry coming into play, the products, be it medicines or medical devices, require extensive financial and time input, starting from the inception of idea till they enter market. On the other hand, their large-scale production with traditional methods asks for another timeline. If the product is too complex, add another resource consuming variable.

The only way to eliminate these resource inputs at such large scales is to adopt state of the art. Starting with medicine/vaccine for diseases, the process begins with researchers trying different combinations of chemicals to attenuate the symptoms and dispense the pathogen. In my opinion, instead of investing in resources and trying to find different combinations, this can be submitted to computational power (**Artificial Intelligence, Machine Learning and Neural Networks**). Use of these technologies will decrease the time spent on finalizing the combinations of chemicals in drug/biologic. Of course, this will need huge amount of **data** for it, which again can be used for forecasting the outcomes of clinical trials.

This leads to another aspect of manufacturing the components. With the advent of **Additive Manufacturing** and its proliferation into the different domains manufacturing highly complex geometry is just effortless. Moreover, as Additive Manufacturing progresses as an effective tool in manufacturing there have been developments in material science, which are focused on making materials more compatible for additive manufacturing. In upcoming decade, the manufacturing would be more interactive and intelligent [4] by combining the power of computation with additive manufacturing to create lighter and resource-effective products.

Although, these technologies have been in use recently, but in my opinion, they are still in their nascent stage with a lot of room to spread in penetrate the industry and would help to bolster the era of health industry. Even looking at a general scenario intelligent manufacturing can only be applied in health industry but also in other industries related to design and production.

3. CURRENT AND NEW PROMISING TECH

There has been a lot of debate on the progress in usage of Artificial intelligence (AI), with two schools of thought like ying and yang. One who oppose the technology and one who want to embrace it for greater good. In a recent interview with Marques Brownlee, a renowned tech youtuber, Bill Gates gave his thoughts on what people think about AI.

In past few years, researchers have found new opportunities in intelligent manufacturing, which include [5]: remote monitoring of real-time process with very low latency; machining of defect free products by efficient planning and scheduling of products; secure and cost-effective maintenance of assets and holistic control of supply chains. Still, the complexity and uncertainty remain questionable aspects and can be major challenges in the coming years.

However, hurdles cannot be left unattended, here is when AI can provide useful ways to ease or maybe resolve these challenges.

Octree-Convolutional Neural Networks (O-CNN) developed by Wang et al, can be very useful in extracting features of 3d models made from low-cost or low-resolution 3D acquisition devices and 3D modeling tools [6]. O-CNN will enable product designers and graphic designers to lower down their acquisition costs while not compromising with the quality of the model. Furthermore, O-CNN can extract features from 3D model and characterize their shapes and parts for performing shape analysis tasks because O-CNN provides an advantage of the local orientation of the shape to enable compact storage and fast computation, which at par with current work. Considering medical devices parts and implants, the aforementioned features of O-CNN will provide extensively smooth and fast manufacturable models.

Talking about manufacturing and traditional machining of parts, currently, the diagnosis of anomalies in machining process of a part cannot be done efficiently because the machining conditions and tooling condition thresholds vary during the processes as they are dynamic in nature. The work of Liang et al. conceptualizes the optimal thresholds for machining processes and tooling using a type of Fruit Fly Optimization (FFO) [7] to detect the anomalies with more accuracy. Tool breakage, spindle failures and tool wear are some of the anomalies which can be challenges in manufacturing of components and parts which involve zero-defect output such as prostheses and medical components. In future, where resources are limited the manufacturing in health industry cannot depend on increased scrap rate but improved product quality and productivity as the health industry is and will be characterized as high value, low volume, and high customization manufacturing domain.

When compared to traditional manufacturing, additive manufacturing (AM) also known as three-dimensional printing (3DP) has its own advantages: it can create topological optimized structures which are identified with high complexity and difficult to manufacture with traditional manufacturing techniques; can be used to create materials with novel characteristics, such as dislocation networks to generate desired part properties; and can be used to save costs for industry by using material wastes [8]. But AM has its own challenges on the defects introduced in the parts made from it: porosity; heavy anisotropy and distortion due to large residual stresses and researchers are still not able to find out a way to recycle metal powders used in metal AM to produce desired characteristics in the parts being produced. Thus, AM parameters are relatively difficult to tune since they impact the microstructure and performance of the printed parts. Qi et al [9] applies Neural-Network Based Machine learning algorithm to build process-structure-property-performance (PSPP) relationship for AM which will be otherwise an extremely difficult task using numerical and analytical methods.

There are three zones where neural networks can be applied to AM: Design for AM (DfAM); in situ monitoring and process-property-performance. DfAM being the first step of model creation as it involves building CAD models for manufacturing. It is quite evident that the part created by the AM machine will differ from the CAD model because of the presence of high level of residual stresses. This can be eliminated by applying a neural network based algorithm to compensate for type of material and model geometry [10]. In situ monitoring can also be done to predict the properties of a layer and control them to eventually estimate the product qualities of the part before it is extracted from the build plate [11]. For example, in Laser Powder bed Fusion or Selective Laser Melting (LPBF or SLM) a successfully trained Neural Network can identify weld pool parameters, plume effect and splatter effect, through different sensing technologies like acoustics [12] or vision system [13].

As mentioned before that evolution of AM as a mainstream manufacturing process has also led to the numerous research opportunities involving material science. Researchers tend to develop new materials or develop parameters for existing materials to be used with additive manufacturing. Some of the materials which will be in limelight in future years would be biocompatible hydrogels and Soft Ionic Polymer-Metal Composites. Cell laden hydrogels can directly be printed and in order to effectively use this approach, cells require a suitable growth environment that preserve cell-cell communication and regulates its biomass. Consequently, hydrogels play a vital role because of their properties that resemble the native extracellular matrix (ECM) and provide structural support while providing apposite growth environment to the cells [15]. Hydrogels are 3D networks composed of hydrophilic polymers, befitted for scaffolding by crosslinking either through covalent bonds or held together via physical intramolecular and intermolecular attractions. Physical and biochemical properties of hydrogels depend on its composition, method used for polymerization, and crosslinking density. Collagen, gelatin, nanocellulose, fibrin, hyaluronic acid, and alginate are some examples of hydrogels used for bioprinting.

On other hand, Ionic Polymer-Metal Composites (IPMC) made of Nafion membranes and platinum electrodes and are generally used in soft robotics and in near future they will be seen as a primary material being used in surgical instruments [16] as they act as sensors.

As fabrication of 3D structures using AM in biotechnology is gaining rapid importance it will not be impossible to predict what future holds for them. As mentioned before, the cells need to communicate and regulate biomass to grow successfully, thus, mechanical properties and feature spacing (permeability) are two important factors to consider for desired cell growth. These two factors can be controlled by layer thickness, delay between spread of two layers and print orientation, although these factors can be determined with experimentally but requires a lot of timely investments. These optimal values can be easily determined by creating an aggregated artificial neural network with optimizations [17].

All my arguments and conjectures basically constitute three major domains of future investment here:

a. Artificial Intelligence
b. Advanced Manufacturing, and
c. Material Science

These domains are worth investing in any industry, but they play a crucial role in health industry.

Although, these technologies are well established but there are four major challenges they are facing:

a. Data: Importance of data acquisition and parsing really important for AI.
b. Sensing: Without enhance hardware and software appropriate and fast data collection is nearly impossible.
c. Control/Optimization: Controlling the properties of materials in manufacturing and closed-loop feedbacks from the system to optimize it in real time with very low latency.
d. Model/Forecasting: Still there are certain latent algorithms for forecasting modeling which requires extreme computational power.

4. STRATEGIC PARTNERSHIPS AND TRAINING

As the time progresses these technological changes will take effect, though there isn't any specific point in time, but these are ought to occur in next decade and a half. As current reports suggest that with majority of people staying at homes the pollution levels around the globe have decreased drastically and the nature is recovering, governments might start taking interest in this trend. If not governments but technological companies like Google, Apple, Microsoft etc. might enforce a mandatory quarantine period where people would work from home.

Majority of the world population is connected through internet and with adoption of intelligent systems as discussed above, work from home might seem a better idea. Information can be shared cloud based sources and server, more importantly, it would pave way for companies to setup data centers which can store huge amount data to be used for Machine Learning purposes or hold cloud data which can be accessed by the user anytime and anywhere. Strategically partnering with the companies maintaining data centers and providing data would be a necessity for other companies.

The overall layout of workplace might not change but companies would start investing in more powerful computing systems and train employees to use them. Companies would also partner with universities and technical schools to train potential employees as well as start extensive internship programs to help them get used to the new technologies they are trying to adopt.

To summarize, the investment of companies seemingly adopting the discussed technologies will include data centers: to store data and serve it to employees and customers, companies would push to timely work from routines; technical training in schools and universities; and more powerful computation machines to run more aggressive and computation intensive algorithms.

REFERNCES

1. Global Trends 2030: Alternative world", by National Intelligence Council
2. Hijioka, Y., E. Lin, J.J. Pereira, R.T. Corlett, X. Cui, G.E. Insarov, R.D. Lasco, E. Lindgren, and A. Surjan, 2014: Asia. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Barros, V.R., C.B. Field, D.J. Dokken, M.D. Mastrandrea, K.J. Mach, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1327-1370.
3. Gates Notes – 2019 Annual Letter, Retrieved from - https://www.gatesnotes.com/2019-Annual-Letter
4. Cai, D., Chen, M., zhu, D., & Liu, J. (2018). Design of intelligent manufacturing big data cloud service platform. Les Ulis: EDP Sciences. doi:http://dx.doi.org.prox.lib.ncsu.edu/10.1051/matecconf/201815308005
5. Liang Gao, Weiming Shen, Xinyu Li, New Trends in Intelligent Manufacturing, Engineering, Volume 5, Issue 4, 2019, Pages 619-620, ISSN 2095-8099, https://doi.org/10.1016/j.eng.2019.07.001.
6. Peng-Shuai Wang, Yang Liu, Yu-Xiao Guo, Chun-Yu Sun, and Xin Tong. 2017. O-CNN: octree-based convolutional neural networks for 3D shape analysis. ACM Trans. Graph. 36, 4, Article 72 (July 2017), 11 pages. DOI:https://doi.org/10.1145/3072959.3073608
7. Y.C. Liang, S. Wang, W.D. Li, X. Lu, Data-Driven Anomaly Diagnosis for Machining Processes, Engineering, Volume 5, Issue 4, 2019, Pages 646-652, ISSN 2095-8099, https://doi.org/10.1016/j.eng.2019.03.012.
8. Barry Berman, 3-D printing: The new industrial revolution, Business Horizons, Volume 55, Issue 2, 2012, Pages 155-162, ISSN 0007-6813, https://doi.org/10.1016/j.bushor.2011.11.003.
9. Xinbo Qi, Guofeng Chen, Yong Li, Xuan Cheng, Changpeng Li, Applying Neural-Network-Based Machine Learning to Additive Manufacturing: Current Applications, Challenges, and Future Perspectives, Engineering, Volume 5, Issue 4, 2019, Pages 721-729, ISSN 2095-8099, https://doi.org/10.1016/j.eng.2019.04.012.

10. Chowdhury, S., Mhapsekar, K., and Anand, S. (December 21, 2017). "Part Build Orientation Optimization and Neural Network-Based Geometry Compensation for Additive Manufacturing Process." ASME. J. Manuf. Sci. Eng. March 2018; 140(3): 031009. https://doi-org.prox.lib.ncsu.edu/10.1115/1.4038293.
11. Yuan, B., Guss, G. M., Wilson, A. C., Hau-Riege, S. P., DePond, P. J., McMains, S., Matthews, M. J., Giera, B., Adv. Mater. Technol. 2018, 3, 1800136. https://doi.org/10.1002/admt.201800136
12. S.A. Shevchik, C. Kenel, C. Leinenbach, K. Wasmer, Acoustic emission for in situ quality monitoring in additive manufacturing using spectral convolutional neural networks, Additive Manufacturing, Volume 21, 2018, Pages 598-604, ISSN 2214-8604, https://doi.org/10.1016/j.addma.2017.11.012.
13. Yingjie Zhang, Geok Soon Hong, Dongsen Ye, Kunpeng Zhu, Jerry Y.H. Fuh, Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion AM process monitoring, Materials & Design, Volume 156, 2018, Pages 458-469, ISSN 0264-1275, https://doi.org/10.1016/j.matdes.2018.07.002.
14. Gu, B.K., Choi, D.J., Park, S.J. et al. 3-dimensional bioprinting for tissue engineering applications. Biomater Res 20, 12 (2016). https://doi.org/10.1186/s40824-016-0058-2
15. Bin Zhang, Lei Gao, Liang Ma, Yichen Luo, Huayong Yang, Zhanfeng Cui, 3D Bioprinting: A Novel Avenue for Manufacturing Tissues and Organs, Engineering, Volume 5, Issue 4, 2019, Pages 777-794, ISSN 2095-8099, https://doi.org/10.1016/j.eng.2019.03.009.
16. Carrico, J.D., Hermans, T., Kim, K.J. et al. 3D-Printing and Machine Learning Control of Soft Ionic Polymer-Metal Composite Actuators. Sci Rep 9, 17482 (2019). https://doi.org/10.1038/s41598-019-53570-y.

APPENDIX

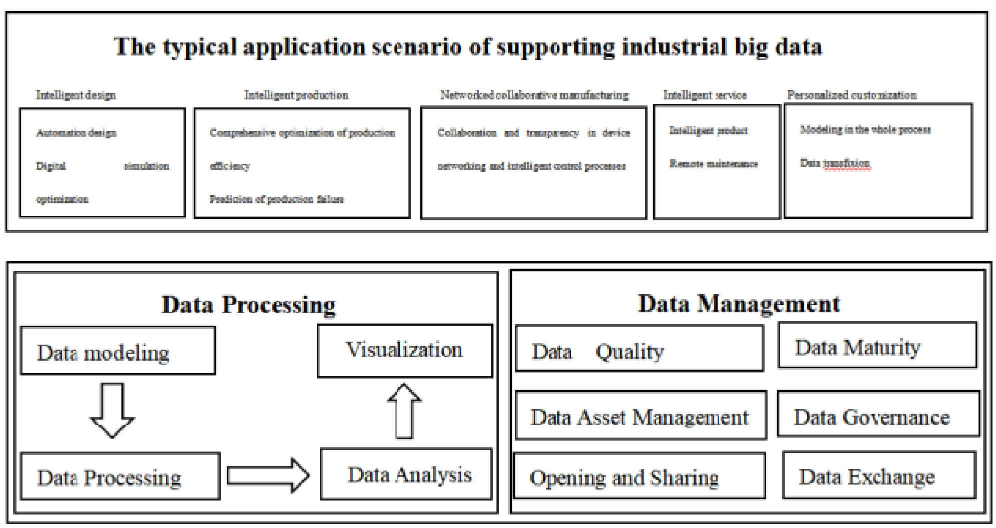
Summaries of papers

1. **Citiation:** Cai, D., Chen, M., zhu, D., & Liu, J. (2018). Design of intelligent manufacturing big data cloud service platform. Les Ulis: EDP Sciences. doi:http://dx.doi.org.prox.lib.ncsu.edu/10.1051/matecconf/201815308005

   Summary: The paper talks about importance of Intelligent Manufacturing and Big Data in future. They delineate a generalized design of Intelligent Manufacturing Big Data Platform. They also talk about its application in design, production, demand forecast, supply chain and development of greener industry.

   Results: The platform is built in three layers:

   a. Data sensing layer: System prescribed to collect, integrate and store data from all sources of the industry.
   b. Data analysis layer: System meant to assess, process and make visual representation of collected data.
   c. Data application layer: Based on data analysis generate better visual description of data on which can aid decision making in industry.



Significance: The results from the platform can influence decisions in research tasks. Furthermore, the results can be used design and product development, making decisions on complex production process, forecasting product demand, optimizing supply chains and developing greener industry with smaller carbon footprint.

Next: It can help in creating an industrial cluster which will aid in expanding product value space by focusing goal on manufacturing and service model. It can also introduce more of a collaborative effort among different companies rather than competition.

2. **Citation:** Peng-Shuai Wang, Yang Liu, Yu-Xiao Guo, Chun-Yu Sun, and Xin Tong. 2017. O-CNN: octree-based convolutional neural networks for 3D shape analysis. ACM Trans. Graph. 36, 4, Article 72 (July 2017), 11 pages. DOI:https://doi.org/10.1145/3072959.3073608

   Summary: The paper talks about the development of octree-convolutional neural network which can parse point cloud data into high resolution 3D models more efficiently than 3D neural networks from cheap and low-resolution 3D data acquisition devices.

   Result: The authors were able to present a 3D model parsed using O-CNN and compare it with original 3D shape and voxelized 3D shape. This demonstrates that with using different data filters O-CCN can be highly effective and efficient.

   Significance: Octree representation algorithms allow high efficacy in data parsing and applying it to create a neural network to identify the object shape can enable compact storage and fast computation.

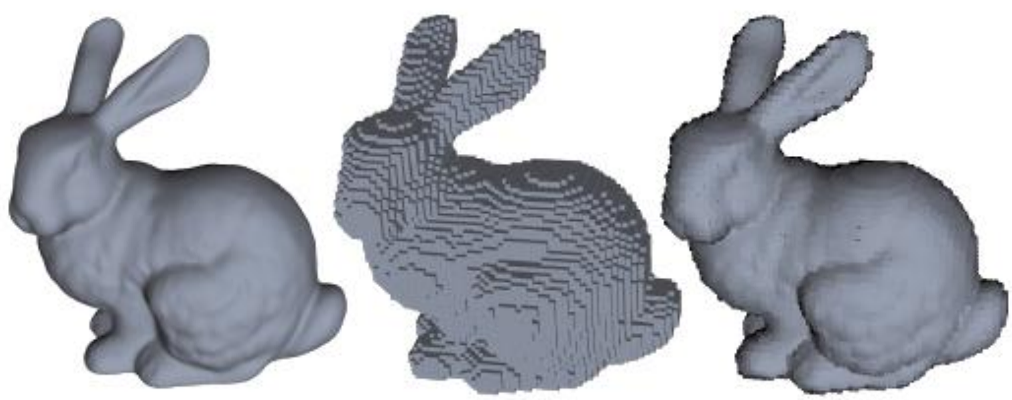


Fig. 3. Left: the original 3D shape. Middle: the voxelized 3D shape. Right: the octree representation with normals sampled at the finest leaf octants.

   Next: O-CCN can in future be used to denoise shapes and applied to shape analysis and processing challenge

3. **Citation:** Y.C. Liang, S. Wang, W.D. Li, X. Lu, Data-Driven Anomaly Diagnosis for Machining Processes, Engineering, Volume 5, Issue 4, 2019, Pages 646-652, ISSN 2095-8099, https://doi.org/10.1016/j.eng.2019.03.012.

   Summary: The paper talks about creation zero-defect manufacturing process using algorithms and AI by optimizing the thresholds for machining process and tooling. They innovated two aspects: Preprocessing mechanisms and fruit fly optimization algorithm to identify optimal anomalies.

   Result: They applied their algorithm to real world usage in order to verify and compare the optimal anomalies with normal production. The anomalies which effect the idea of zero-defect manufacturing were identified as tool wear and tool breakage with a new abnormal situation as long-time air cutting.

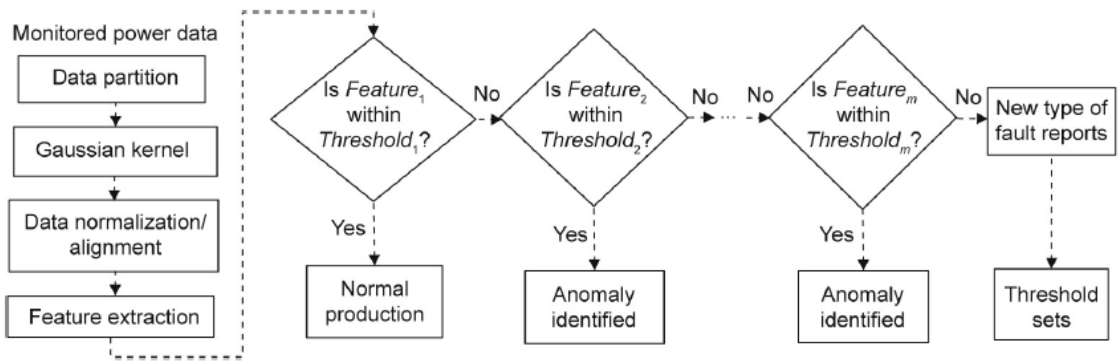


Fig. 3. The anomaly diagnosis process.

   Significance: Anomalies generally increase the down time of a machine thereby decreasing production quantity. This paper signifies an important way to diagnose anomalies beforehand to eliminate them.

   Next: Researchers will apply neural networks and deep learning algorithms to improve computation and thus the system performance.

4. **Citation:** Xinbo Qi, Guofeng Chen, Yong Li, Xuan Cheng, Changpeng Li, Applying Neural-Network-Based Machine Learning to Additive Manufacturing: Current Applications, Challenges, and Future Perspectives, Engineering, Volume 5, Issue 4, 2019, Pages 721-729, ISSN 2095-8099, https://doi.org/10.1016/j.eng.2019.04.012.

Summary: This paper discusses the concept of agile manufacturing which combines additive manufacturing with neural networks (NNs). This paper gives a comprehensive overview of current situation in applying NNs to complete AM process.

Results: This is a concept-based peer-reviewed paper. Results shown is about use of Machine learning techniques which can be used to enhance additive manufacturing process and optimize their usage in different fields. Results establish the use of NNs in DFAM, in situ monitoring of manufacturing processes and prediction of properties of a product based on process and performance where accuracies can reach up to 93.94%.

Table 1
NN application to build process–property–performance linkage.

AM technique	Processing parameters	Property/performance	Ref.
FDM	Layer thickness, orientation, raster angle, raster width, air gap	Compressive strength	[39]
FDM	Layer thickness, orientation, raster angle, raster width, air gap	Wear volume	[40]
FDM	Orientation, slice thickness	Volumetric error	[41]
FDM	Layer thickness, orientation, raster angle, raster width, air gap	Dimensional accuracy	[42]
FDM	Layer thickness, orientation, raster angle, raster width, air gap	Dimensional accuracy	[43]
BJ	Layer thickness, printing saturation, heater power ration, drying time	Surface roughness	[44]
BJ	Layer thickness, printing saturation, heater power ration, drying time	Shrinkage rate (*Y*-axis)	[44]
BJ	Layer thickness, printing saturation, heater power ration, drying time	Shrinkage rate (*Z*-axis)	[44]
SLS	Laser power, scan speed, scan spacing, layer thickness	Density	[45]
SLS	Laser power, scan speed, scan spacing, layer thickness	Dimension	[46]
SLS	*Z* height, volume, bounding box	Build time	[47]
SLS	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	Shrinkage ratio	[48]
SLS	Layer thickness, laser power, scan speed	Open porosity	[49]
SLS	Laser power, scan speed, hatch spacing, layer thickness, powder temperature	Tensile strength	[50]
SLS	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	Density	[51]
SL	Layer thickness, border overcure, hatch overcure, fill cure depth, fill spacing and hatch spacing	Dimensional accuracy	[52]
LMD	Laser power, scanning speed, powder feeding rate	Geometrical accuracy	[53]
EBM	Spreader translation speed, rotation speed	Volume, roughness	[54]
WAAM	Bead width, height, center distance of adjacent deposition paths	Offset distance	[55]

SL: stereolithography; LMD: laser metal deposition; WAAM: wire and arc additive manufacturing.

Significance: This study is important to establish a connection of computation into manufacturing domain which will help in delineating myriad of options to improve the manufacturability of products.

Next: NNs in future can help in data collection and interoperability of application programming interfaces; in sensing of difference in situ or ex situ process control; Control/Optimization of the processes; linkages of process-property-performance chains and modeling forecasting.

5. **Citation:** Chowdhury, S., Mhapsekar, K., and Anand, S. (December 21, 2017). "Part Build Orientation Optimization and Neural Network-Based Geometry Compensation for Additive Manufacturing Process." ASME. J. Manuf. Sci. Eng. March 2018; 140(3): 031009. https://doi-org.prox.lib.ncsu.edu/10.1115/1.4038293.

Summary: This paper provides an insight about the how the part orientation and the cyclic cooling and heating induce quality concerns in an additively manufactured part. This paper talks about the use of artificial neural networks in mitigating these concerns.

Result: Two Step methodology used to confront the concerns in part orientation and cyclic cooling and heating. First, based on DFAM guidelines to determine build orientation to maximize manufacturability, a weighted multiparameter optimization model. Second, an ANN geometry compensation algorithm is applied at optimal orientation using an objective function.

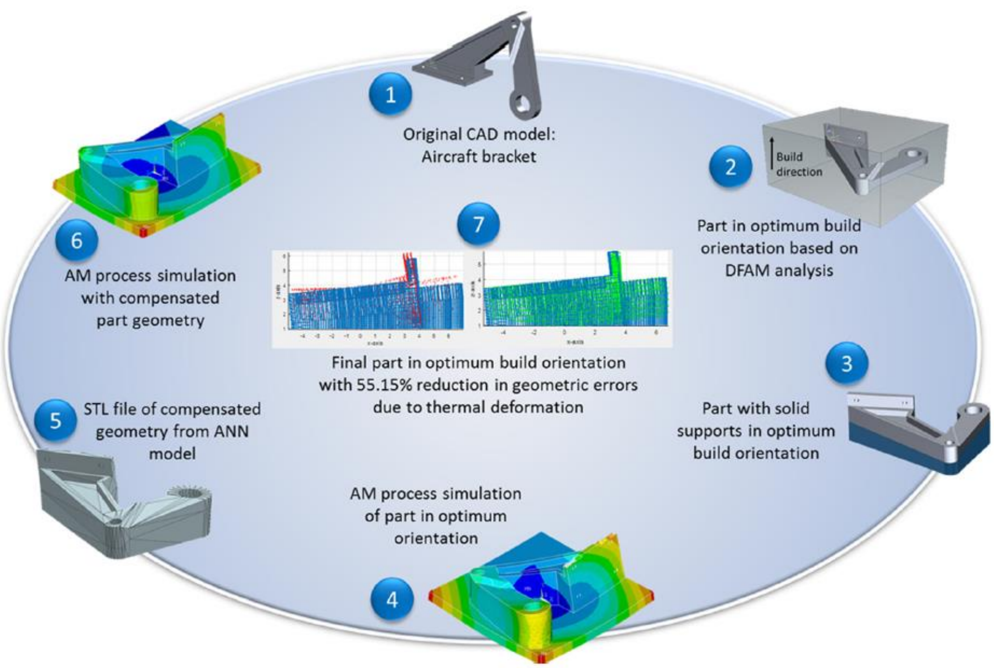


Fig. 27 Overview of the two-step methodology for the test part

Significance: The approach can be applied to any finite element based thermal models predict deformation in any print orientation of the part. Secondly, the orientation can be optimized in order to control part properties and maximize manufacturing.

Next: This approach can be further be used by including more parameters in objective function to improve manufacturability.

6. **Citation:** S.A. Shevchik, C. Kenel, C. Leinenbach, K. Wasmer, Acoustic emission for in situ quality monitoring in additive manufacturing using spectral convolutional neural networks, Additive Manufacturing, Volume 21, 2018, Pages 598-604, ISSN 2214-8604, https://doi.org/10.1016/j.addma.2017.11.012.

Summary: The paper investigates acoustic emissions for quality monitoring of additively manufactured part. Using machine learning and sensitive acoustic emissions they were able to detect anomalies in AM part.

Result: Neural Networks both Spectral and conventional were used to classify features from different additive manufacturing with an accuracy of 83% for high quality workpiece, 85% in medium quality workpiece and 89% in low quality workpiece.

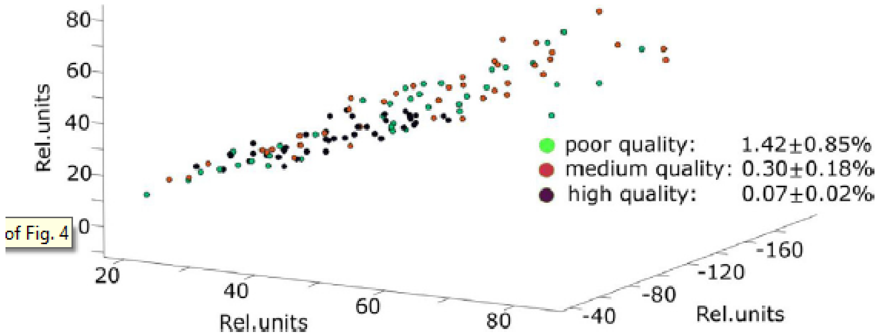


Fig. 4. Projection of the acoustic features into a 3D feature space using principle component analysis (PCA). The visualized dataset includes thirty features from each quality level.

Table 1
Classification tests accuracy results for the SCNN (conventional CNN).

Ground truth / Test category	Poor quality	Medium quality	High quality
Poor quality (1.42 ± 0.85 %, 800 mm/s)	89 (62)	4 (19)	7 (19)
Medium quality (0.3 ± 0.18 %, 300 mm/s)	5 (25)	85 (53)	10 (22)
High quality (0.07 ± 0.02 %, 500 mm/s)	8 (20)	9 (17)	83 (63)

Significance: Additive manufacturing has not been a mainstream industrial process because of the defects produced in the parts which directly resonates with part quality and their poor diagnosis. This is one of the diagnostic techniques used to find these defects.

Next: This technique can further be applied to other AM processes as it was only tested on Powder Based SLM.

7. **Citation:** Yingjie Zhang, Geok Soon Hong, Dongsen Ye, Kunpeng Zhu, Jerry Y.H. Fuh, Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion AM process monitoring, Materials & Design, Volume 156, 2018, Pages 458-469, ISSN 0264-1275, https://doi.org/10.1016/j.matdes.2018.07.002.

Summary: This paper focuses on in situ identification of melt pool, plume and spatter effects using a vision system. The output from the vision is then fed to SVM and CNN to identify these effects and detection accuracies for both the classification techniques were compared.

Results: The experiments were able to achieve a classification accuracy of 90.1% for the melt pool, plume and spatter. Comparison between the SVM and CNN yielded a high accuracy of 92.7% CNN.

Table 4
Mean classification accuracy (MCA) for different classes.

Input	Melt pool features	Plume features	Spatter features	17 features from three objects		33 features from three objects		Raw data
Classifier	SVM	SVM	SVM	SVM	PCA + SVM	SVM	PCA + SVM	CNN
MCA (%)								
Class-1	76.1	89.0	88.0	94.9	94.6	96.6	96.0	**98.2**
Class-2	79.3	60.3	64.7	87.2	83.5	84.0	84.3	**91.6**
Class-3	85.5	68.8	60.1	**92.0**	86.9	88.4	89.9	88.4
Average MCA (%)	80.3	72.7	70.9	89.1	88.3	89.6	90.1	**92.7**

Significance: The melt pool, plume and spatter affect the final mechanical and physical properties of the parts; hence these techniques can be used to predict part properties as well as control them.

Next: Vision techniques can be further used to determine real-time defect analysis in manufacturing parts and quality monitoring in other industrial application as well with the use of high computation power.

8. **Citation:** Gu, B.K., Choi, D.J., Park, S.J. et al. 3-dimensional bioprinting for tissue engineering applications. Biomater Res 20, 12 (2016). https://doi.org/10.1186/s40824-016-0058-2.

   Summary: This paper summarizes the advantages and disadvantages of all the 3DP techniques used in bioprinting of scaffolds for tissue engineering. This paper also delineates the common materials used in 3D Bioprinting.

Result: Disadvantages and advantages of each printing method were discussed concluding with inkjet 3DP as the best one because bioinks can be cell laden which is not possible with other techniques.

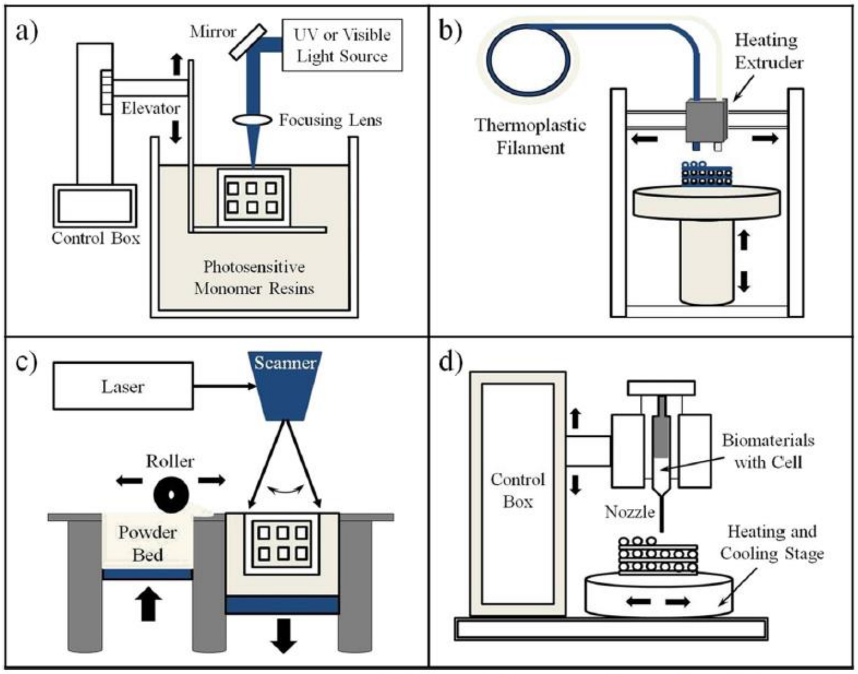


Fig. 2 Schematics of various 3D bioprinting for tissue engineering applications; **a** Vat photopolymerization, **b** Fused filament fabrication, **c** Selective laser sintering, **d** Inkjet 3D printing

Significance: It provides a holistic view of all the techniques that can be used to create scaffolds narrows down to one technique and the best materials that are being used in the field currently.

Next: Development of materials for 3D Bio Printing is the next step as the we need different techniques to be qualified for operating in the field.

9. **Citation:** Bin Zhang, Lei Gao, Liang Ma, Yichen Luo, Huayong Yang, Zhanfeng Cui, 3D Bioprinting: A Novel Avenue for Manufacturing Tissues and Organs, Engineering, Volume 5, Issue 4, 2019, Pages 777-794, ISSN 2095-8099, https://doi.org/10.1016/j.eng.2019.03.009.

   Summary: This paper also summarizes different 3D bioprinting techniques but extend the application to analyze the usage of bioinks with different forms of printing techniques. This paper also describes the use of techniques to create different type of body tissues with experiments to create hollow tissues.

Results: Hollow tissues were successfully created using 3DP with stem cell laden bioink. Novel biomaterials can be tuned for mechanical properties to produce different tissues.

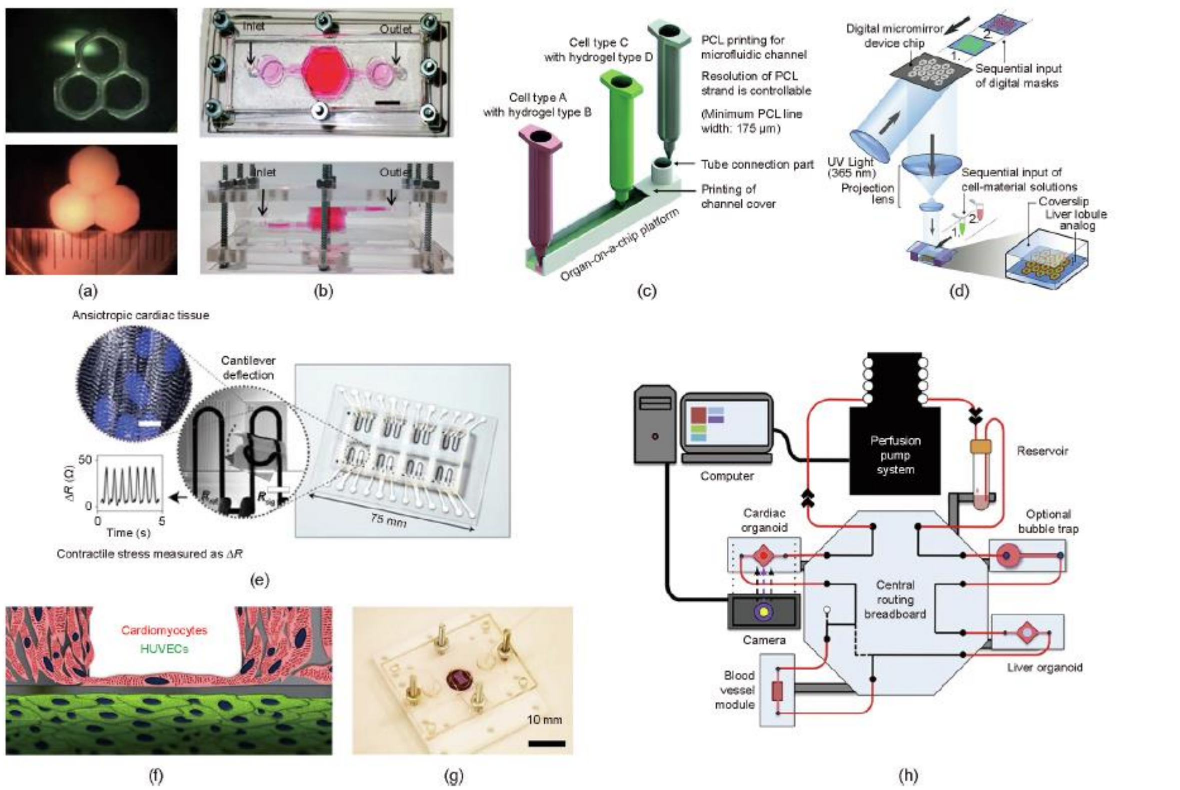


Fig. 10. 3D bioprinting of organs-on-chips. (a–d) Liver-on-a-chip: (a) A multilayer heterogeneous hepatic tissue with a thickness of 250–500 μm; (b) a bioreactor containing a 3D bioprinted hepatic construct for the long-term culture of HepG2/C3A spheroids; (c) a one-step fabrication approach by multi-nozzle bioprinting for fabricating a liver-on-a-chip; (d) a DLP-fabricated 3D triculture model that embeds hiPSC-HPCs with hUVEC and adipose-derived stem cells in a microscale hexagonal architecture [26]. (e–g) Heart-on-a-chip: (e) A microphysiological device constructed by printing six functional bioinks and integrating soft strain gauge sensors for drug toxicity testing; (f, g) an organoid fabricated by seeding cardiomyocytes into an endothelialized hydrogel scaffold was embedded into a bioreactor for cardiovascular toxicity evaluation. (h) Schematic of a multi-organoid body-on-a-chip. (a) Reproduced from Ref. [138] with permission of Fedn of Am Societies for Experimental Bio, © 1987; (b) reproduced from Ref. [18] with permission of IOP Publishing, © 2009; (c) reproduced from Ref. [19] with permission of Royal Society of Chemistry, © 20116; (e) reproduced from Ref. [20] with permission of Springer Nature, © 2016; (f, g) reproduced from Ref. [83] with permission of Elsevier, © 2016; (h) reproduced from Ref. [137] with permission of Elsevier, © 2016.

Significance: The stem cell technology combined with 3DP can enhance better functionality of organs-on-chips to ease out the growing demand of transplantable organs.

Next: Further investigations are needed to determine the longevity of 3DP architectures and vascularization.

10. **Citation:** Carrico, J.D., Hermans, T., Kim, K.J. et al. 3D-Printing and Machine Learning Control of Soft Ionic Polymer-Metal Composite Actuators. Sci Rep 9, 17482 (2019). https://doi.org/10.1038/s41598-019-53570-y.

    Summary: In this paper the authors present the additive manufacturing of robotic actuators using soft ionic polymer material composite (IPMC) for soft robotics. The control of the robot based on machine learning model is also presented and the control distance was measure in normalized distances.

Result: Bayesian optimization was used to optimize the test gait of the crawling robot whose limbs were constructed with soft IPMC of platinum and Nafion. With using this machine learning algorithm, the robot was able to achieve the target value of 95% of the normalized distance with fewer trials than a finite difference policy gradient method.

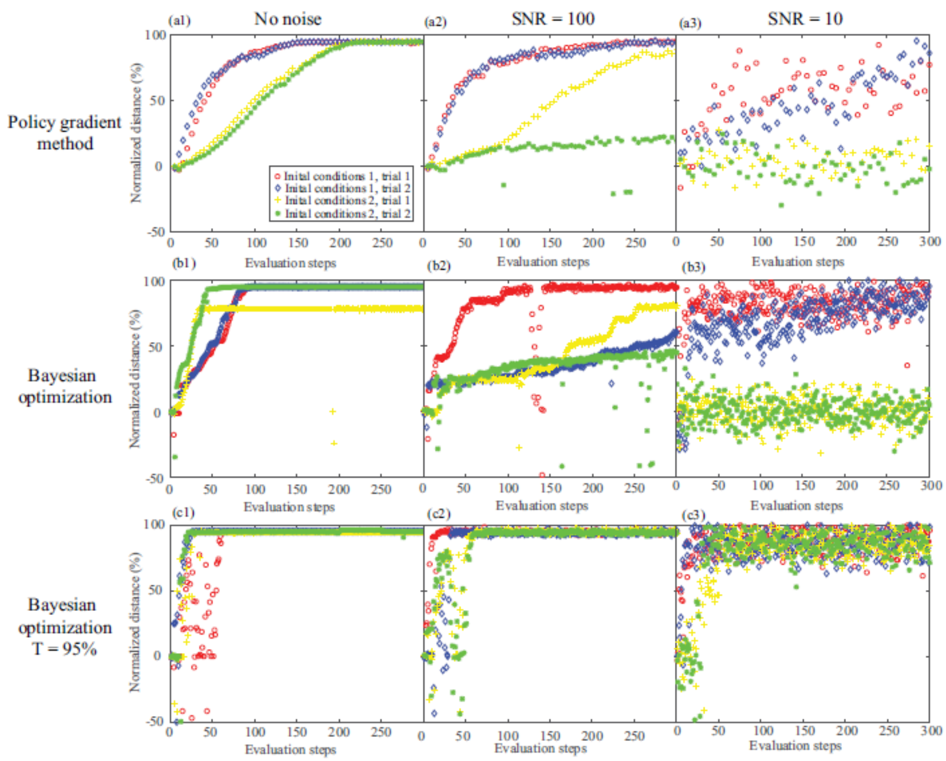


Figure 6. Policy gradient method using finite-difference gradient estimation vs. Bayesian optimization using probability of improvement (PI) acquisition function, with multiple trials from different ICs and signal to noise ratios (SNR)s: (**a1**) policy gradient with no noise, (**a2**) policy gradient with SNR = 100, (**a3**) policy gradient with SNR = 10, (**b1**) Bayesian optimization with target equal to maximum of training data with no noise, (**b2**) Bayesian optimization with target equal to maximum of training data with SNR = 100, (**b3**) Bayesian optimization with target equal to maximum of training data with SNR = 10, (**c1**) Bayesian optimization with target equal to 95% maximum possible distance with no noise, (**c2**) Bayesian optimization with target equal to 95% maximum possible distance with SNR = 100, (**c3**) Bayesian optimization with target equal to 95% maximum possible distance with SNR = 10.

Significance: IPMCs are used in biomedical applications as well as in soft robotics which find their significance in different fields. The technology signifies unsupervised working methods for soft robots.

Next: With further research the optimal printing resolution can enable to reduce the displacement of the robot as the increased printing resolution increases the increases the failure to produce thin walled actuators.