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DIGITAL TWIN: MANUFACTURING EXCELLENCE THROUGH VIRTUAL FACTORY REPLICATION

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ABSTRACT
Injection molding industry has evolved over decades and became the most common method to manufacture plastic parts. Monitoring and improvement in the injection molding industry are usually performed separately in each stage, i.e. mold design, mold making and injection molding process. However, in order to make a breakthrough and survive in the industrial revolution, all the stages in injection molding need to be linked and communicated witheachother.Anychangesinonestagewillcauseacertaineffectinotherstagebecausethere is a correlation between each other. Hence, the simulation should not only based on the input of historical data, but it also needs to include the current condition of equipment and prediction of future events in other stages to make the responsive decision. This can be achieved by implementing the concept of Digital Twin that models the entire process as a virtual model and enables bidirectional control with the physical process. This paper presented types of data and technology required to build the Digital Twin for the injection molding industry. The concept includes Digital Twin of each stage and integration of these Digital Twin model as a thoroughgoing model of the injection molding industry.

Keywords: Monitoring, molding industry, Dig.

I. INTRODUCTION

Injection molding is one of the most important and common manufacturing process to produce plastic parts in high volume and low cost. Products that manufactured using injection molding vary widely in the geometry complexity, size, materials and application in varies industry. Integration of smart manufacturing concept into injection molding known as smart injection molding which implement the Internet-of-Things(IOT)ininjectionmoldingthatenablesdatacollection,communicationandanalytics to achieve flexibility in process and improve production efficiency.

Injection molding industry covers three main stages i.e. mold design, mold making and the injection molding process. The design of injection mold is an important stage because it is costly to do re-design and modification of mold in the future mass production. In current practice, mold design and making are perform either in-house or outsourcing. Mold designer gathers information on part, material and machine to determine the type of mold, layout of the moldin mold design. Once the design is completed, the mold designer will conduct the simulation using mold simulation software and the final design will sendtomoldmakingstage.Moldmakingstageconsistsofelectrodedesignandmanufacturingformold insert, machining of mold components, assembly of mold and testing of the mold in machine. Tight tolerance and wide variety of processes involved increase the complexity of production planning. An efficient production planning is necessary in order to ensure the completion of mold on time. Finally, the production of plastic partsin injection molding process. It begins with production planning based on demands, machine and mold availability. During the injection molding process, personnel in the operation perform the control and monitoring as well as optimization

of machine parameters setting and the inspection on molded parts. The production data such as parameter setting, machine and mold condition, and rejection will be input and updated from time to time to production planning for adjustment of schedule and maintenance schedule. Real-time control and monitoring is almost impossible because of the large volume of processing data required and difficulty to perform real-time inspection.

Every stage in injection molding industry affects each other on the performance of the production of molded parts. Various data in the entire injection molding industry, including mold design, mold manufacturing and the injection molding process need to be linked to achieve more efficient, smart and sustainable manufacturing environment.[1] Hence, the real-time bidirectional information flow between these stage sis crucial to improve the performance from the aspect of quality, time and cost. In addition, are view report about the state of manufacturing conducted by General Electric(GE)in2017mentioned that there are not enough skilled people in manufacturing factories to fill manufacturing jobs and keep up with demand. This situation motivates the industry to shift towards smart manufacturing. The merging of Internet-of-Things (IOT) and the concept of Digital Twin enables the real-time data-driven manufacturing in various stages via convergence between physical and virtual production system. Therefore, this paper presented the application of Digital Twin concept in every stage of injection molding industry and the integration of each Digital Twin model that brings all the experts and data from each stage together to achieve complete and powerful insight in injection molding industry

II. CONCEPT OF DIGITAL TWIN

Digital Twin plays important role in the 4th Industrial Revolution because it enables the combination of informationtechnologyandoperationtechnologytocreatenewvaluebylinkthepreparatoryproduction stage with real production. [3] The Digital Twin concept model introduced by Dr. Michael Grieves contains three main parts: physical products in real space, virtual products in virtual space and the connections of data and information that connects the physical and virtual space. [2] Digital Twin can be defined as a replication of real physical production system in digital model, which are used for system optimization, monitoring, diagnostics and prognostics using integration of artificial intelligence, machine learning and software analytics with large volume of data from physical systems.

Digital Twin model has five enabling components – sensors and physical assets from physical system, integration, data and analytics in the digital model. Data consists of data from enterprise and operational and environmental data from physical system obtained using sensors distributed in physical system. The sensors allow bidirectional data communication in real-time between physical system and virtual system using integration technology, which includes communication interface and security. Then the Digital Twin uses the analytics techniques to analyze the data for defined purposes and provides responsive action based on simulation result to physical asset for further action. [4] With the Digital Twin, the operation in a single machine as well in the interconnected system are visible to everyone who has authority to access the system, i.e. manufacturing, procurement, warehousing , transportation and logistics. Digital Twin allows the manufacturers to see how the physical system is performing by looking all the data in the manufacturing execution system. The analytics techniques in the Digital Twin model include what-if analysis and predictive analysis to simulate the real-time conditions in the physical system and predict the future state of the systems. The conceptualization, comparison and collaboration capability of Digital Twin enables us to conceptualize the manufacturing process visually, compare the option and outcome, and then finally collaborate with other manufacturing section.

General Electric (GE), Siemens and ANSYS introduced a series of platform to build the Digital Twin. Currently, this technology has been implemented in a ero space industry, wind-turbine powerplant and automotive industry for performance improvement and operational inefficiency prediction. [5] For example, GE has buil t Digital Twins of jet engine that can achieve power optimization, monitoring and diagnostics of jet engine. DXC Technology built a Digital Twin for hybrid car manufacturing process to predict the performance of car before committing the changes in the manufacturing process.

III. HOW TO CREATE A DIGITAL TWIN

Creating a digital twin starts with establishing new pipelines of manufacturing data. We can automate the collection f data, for example, from materials and design. When integrated with historical operations performance data, we now have what we need to support a digital twin. The next step is to take the manufacturing process and model it using rules. But instead of using retrospective models, we use prescriptive models. Retrospective models, like those commonly used in predictive modeling, try to calculate the future according to past trends. Models such as this have been successful in some areas of manufacturing prediction, but they focus on optimization rather than on break through innovation. With the digital-twin approach, we build stochastic simulations, or prescriptive models. We do this by creating rules that map from design to performance and add randomness to simulate risk. The prescriptive data from the simulations shows how new products will work. By analyzing it, we can detect design flaws early. We can predict and minimize cost. And wecanusethismountainofintelligencetobuildimprovedproductsinthefuture.Because randomness is inherent in the model, we can simulate the kind of uncertainty encountered in the real world. And since computing power is cheap, we can afford to run millions of scenarios, anticipating an entire spectrum of possible outc omes, rather than just as in gle expected result. Infact, we can learn as much from the digital twin as we can from the real-world original.

The Internet of Things (IOT) adds another layer of insight. We can augment the manufacturing process with sensors and automatically generate data about operations, performance and maintenance. By using industrial machine learning— a scalable solution for in gesting data, building algorithms and deploying the minto production—we can turn the streaming variant of the digital twin into a continuous source of manufacturing insight.
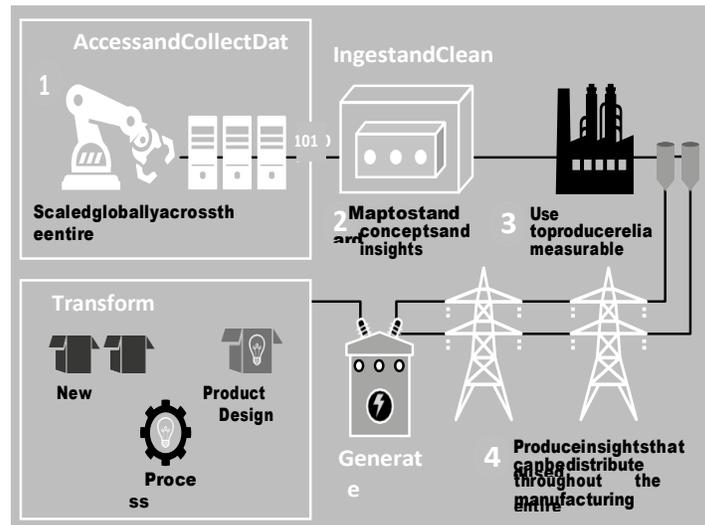

Figure 2. This is the roadmap from data streams to prescriptive insights

IV. DIGITAL TWIN AND IOT

Digital twin really sits in the continuum of the IoT. If we agree that the foundation of IoT consists of connectivity, sensors and analytics, then predictive maintenance becomes an established IoT application. Predictive maintenance is case-based reasoning enabled by data. The digital-twin approach handles this by incorporating product data, including maintenance history, from design to operation and beyond. GE is pilotinga "digital wind farm" concept used to inform the configuration of individual wind turbines prior to procurement and construction. Once the farm is built, each virtual turbine is fed data from its physical equivalent, and software adjusts turbine-specific parameters, such as torque of the generator and speed of the blades, to optimize power production at the plant level. The hope is to generate 20 percent gains in efficiency. PTC has developed" smart connected product

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life-cycle management(PLM)" software called "Windchill." ASw iss solar panel manufacturing company, Oerlikon, uses Wind chill to automatically track system metrics and keep account managers apprised of the condition of client systems. PTC describes it as a FRACAS process: a failure reporting, analysis and corrective action system. Dassault Systèmes has built an aerospace- and defense-specific manufacturing operations management product called "Build to Operate." The solution can monitor, control and validate all aspects of manufacturing operations, ranging from replicable processes and production sequences to the flow of deliverables through out their supply chain—and on a global scale. Air bus Helicopters has deployed this system for current and future helicopter rmanufacturing. Although the application of digital-twin technology is still in its early stages, the possibilities for the manufacturing industry are tremendous. The ability to design, produceandrepairproductswiththeguidingintelligenceofdata-drivensimulations will be a game-changer that leads to greater efficiency and bigger innovations in the field.

V.   EVOLVED DIGITAL TWIN, EXTENDED BENEFITS

As digital twins get more capable, they are being applied to a growing number of uses, from designing and testing products and processes to monitoring day-to-day operation and conducting maintenance.

5.1 Accelerating Innovative Product Design
Using realistic digital models, product designers can quickly and inexpensively prototype new ideas and simulate a variety of what-if scenarios involving system interactions, product testing, and customer experience. For example, automaker Maserati has used virtual modeling and simulation to reduce the number of expensive, real-world prototypes, wind tunnel tests, and test drives, cutting vehicle development time by 30 percent[16]. French supermarket chain Intermarket uses data from IoT-enabled shelves and sales systems to create a digital twin of a brick-and-mortar store, enabling managers to get real-time insight on stocks and test the efficacy of different store layouts before implementing[17].

5.2 Designing More Efficient Processes
Using digital twins to model complex processes allows companies to identify inefficiencies and ways to address them. GE created digital models of sup- ply chain and factory processes at its Nevada facility that improve inventory management by helping leadership make thousands of data-informed decisions.18 Maserati digitally modeled its production line to improve the positioning of factory robots and eliminate inefficient movement, improving facility throughput by a factor of three.19 In health care, Dassault Systems is building a "library" of realistic human heart simulations that physicians can consult to better understand a patient's condition in real time and compare reactions to different treatments[20]

5.3 Optimizing Day-To-Day Performance
By continuously capturing vital operational metrics, enterprises can monitor and optimize product or process performance in real time. Digital twins of the medical facilities of 50 hospitals, for example, are expected to improve patient experience by identifying the busiest areas and times of day in each hospital and simulating solutions to resolve congestion[21].

5.4 Enabling Predictive Maintenance
Digital twins can watch for imminent risks such as equipment breakdown, enabling operators to proactively mitigate issues and reduce both un- expected maintenance shutdowns and scheduled but unnecessary maintenance procedures. For ex- ample, GE's aircraft engines' digital twins combine sensor, performance, and environmental data with insights from similar engines. The digital twin can then predict the life span of various engine components under different scenarios. This enables teams to make informed maintenance decisions, resulting in reduced turnaround time. By using these digital twinned engines in their fleet, one airline was able to reduce the number of maintenance shop visits, saving millions of dollars in unnecessary service overhauls.

5.5 Planning For Large-Scale Infrastructure Changes

Digital twins can help with planning for the impact of changes in urban infrastructure. Modeling the behavior of individual people or vehicles, for instance, can make it possible to predict the emergence of collective behavior arising from cascading effects due to disasters or infrastructure failures. They can also help visualize and understand the impact of large-scale infrastructure or other projects such as wireless rollouts, the construction of stadiums, or the redevelopment of city neighborhoods. For example, this could make it possible to design better emergency response systems or more resilient infrastructure .

VI.   APPLICATION OF DIGITAL TWIN IN INJECTION MOLDING MOLD DESIGN AND MANUFACTURING

ThissectionpresentstheneedsofDigitalTwinateverystageininjectionmoldingindustryandhowthe Digital Twin connects with each other to build, operate and enhance the performance at each stage. Figure 1 shows the overview of information flow in the injection moldingindustry.
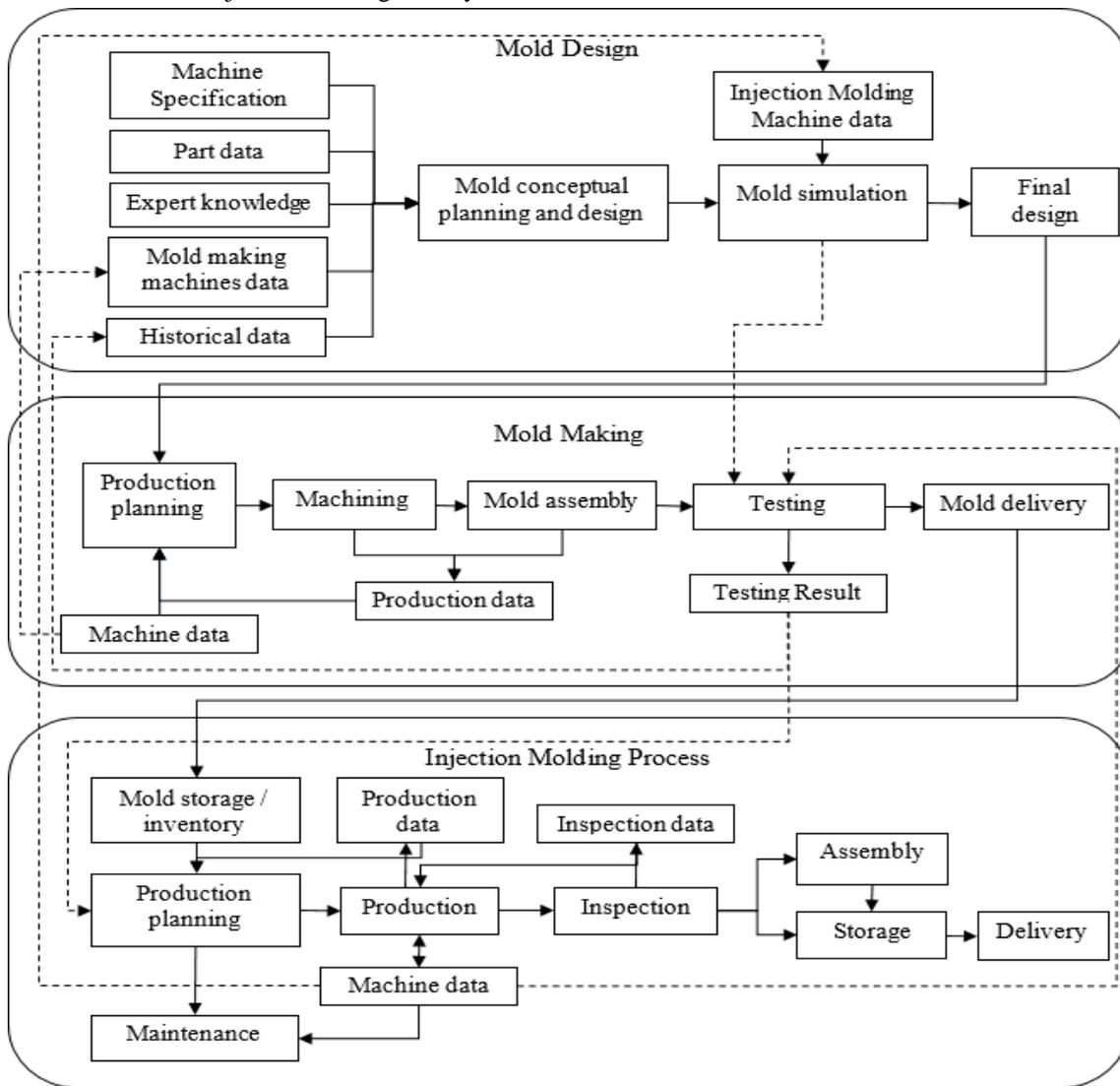

Figure1.Overview of information flow in injection molding industry

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6.1 Injection mold design

Input information of part drawing and specification of material, molding machine specification and other tool specification such as type of mold, runner system, gate, use of robotics and estimated cycle time are necessary when design the mold. Mold designer has to be experienced enough to take all these considerations and the capability of mold making production to produce the designed mold. Mold design and simulation software such as Mold flow enables designer to design, simulate and analyze the mold designed and the part produced. The data input to simulation is based on the technical specification provide by the material supplier and machine manufacturer. However, in practice, the condition of a specific machine in production varies overtime and this will cause the result from simulation differ from the real production. Therefore, in order to obtain accuracy and reduce resetting time during moldtesting, the simulation has to be conducted using data from current condition of injection molding machine which to be used. These data can be obtained from the database of the Digital Twin model of the machine in the injection molding production. In addition, lead-time of mold design and making determine the lead-time of product to market. Continuous data input of machines for mold making process helps mold designers to gather the updated information on the machine condition and adjust design accordingly with the capability and availability of machining machines to avoid production delays due to the toolor machine break down during moldmaking. The final design of the mold will act as Digital Twin model of the mold and can be virtually installed in Digital Twin model of injection molding machine for future production planning and real-time process simulation.

6.2 Injection mold manufacturing

Once the mold design is completed, the detailed drawing of the mold will save in the database and mold- making production will retrieve the drawings for mold making process. Mold making mainly consists of machining of the parts, assembly and testing. Machining of mold components start with cutting of raw material, milling and lathe, wire-electrical discharge machining (WEDM), EDM and polishing. Each of the machine and tools has its own Digital Twin model. With the Digital Twin models of the machines, the overall physical production of mold making process can be visualized and simulate the production for production planning. During production, sensors distributed at each machine will send real time data to the Digital Twin models for production monitoring, quality prediction and prediction of machine condition for preventive maintenance scheduling. These data will update and store in each Digital Twin model and will be used for future mold design process. In current practice, the production of mold making are done manually. However, because of the heavy weight of the mold, high variety number of components to be manufactured and assembled, application of human robot collaboration (HRC) systems is proposed in mold making process.Figure2 shows the proposed framework of HRC systems in mold making. Simulation of the HRC systems is required to determine the collaborative ask sequence, robot model selection and robot effect or selection. Hence, the integration of the Digital Twin models of the human workers and the robots into the Digital Twin models of machines are necessary. Adaptive capability of robot to human working condition is one of the important issue in HRC systems. The Digital Twin models can analyze, simulate and predict the human worker's condition with the continuous input of human-robot unit data, and then input the result to robot for motion adjustment to adapt with the human worker's condition from time to time.
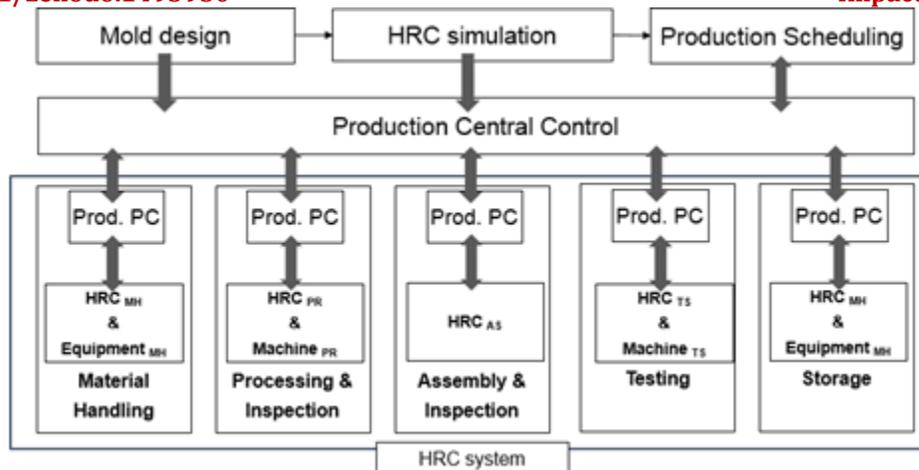
Figure 2. This is the roadmap from data streams to prescriptive insights

6.3 Application of digital twin in injection molding process
Many research related to injection molding process focus on the optimization on process parameter and quality, but the trend of research is moving towards real-time process optimization, process monitoring, and prediction of quality defects. Application of Digital Twin concept in injection molding can help to achieve these objectives. Figure 3 illustrates the concept of Digital Twin in injection molding process.

Virtual production consists of the Digital Twin model of every single machine and equipment includes mold, material handling equipment and automated visual inspection system. Each of the machine is unique although they have the same machine specification and model because the machine condition will change when the production proceeds from time to time and this will cause instability in the performance of the molding machine. Besides, it is difficult to ensure the consistency of material supply. These problems lead to the inconsistency in quality of molded part. Before the production, the initial parameters are set according the result from mold testing in mold making stage. The Digital Twin models of automated inspection system also used to determine and select the corresponding image- processingalgorithmandinspectionequipmentsetupbeforetheproductionstarts.Duringtheproduction, sensors distributed in each physical machine provides updated production data to manufacturing execution system and virtual models. The virtual model feedback the responsive action to physical production for production plan adjustment. Theme asurement of machine condition such as pressure and temperature corresponding to the machine parameter setting and the real-time result from automated inspection system are input to computational model of Digital Twin for the purpose of process optimization and quality prediction. These data can further analyze and generate maintenance schedule for mold and injection molding machine.
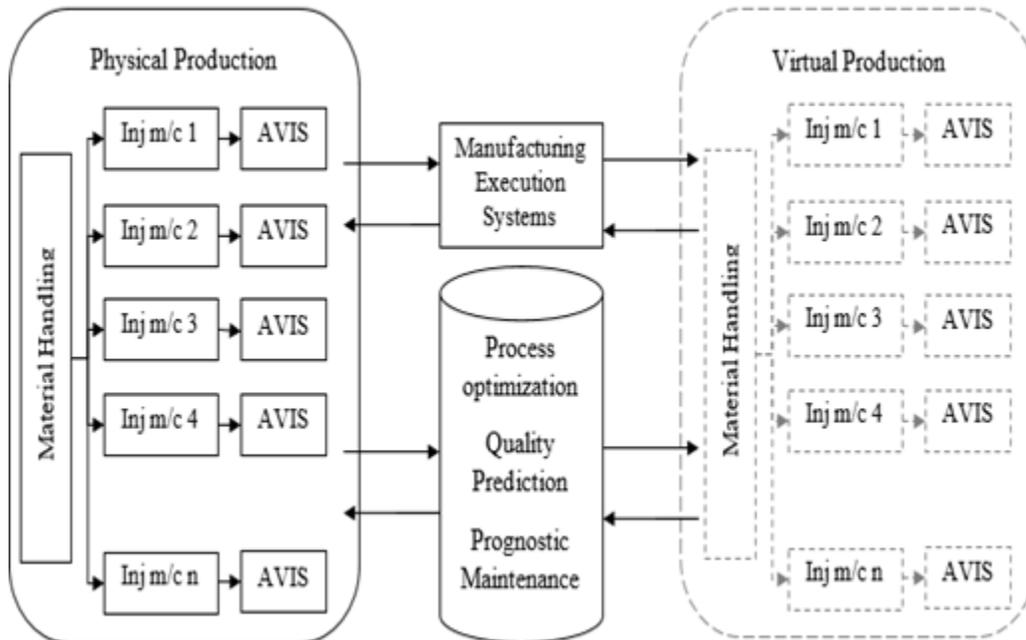
Figure 6. Digital Twin of injection molding process. (Injection m/c: injection molding machine; AVIS: automated visual inspection system)

VII.   CONCLUSION

This paper presented the application of Digital Twin concept in injection molding industry from mold design to mold making and finally injection molding process. Technology such as Internet-of-Things (IoT) and Cyber Physical System(CPS) play important role in Digital Twin concept. Some problems in realization of the Digital Twin in injection molding such as manual acquisition of data, implementation of sensors in injection molding machine, development t of real-time automated visual inspection systems, optimization and predictionanaly tics model are yet to be solved to complete the Digital Twin application in injection molding industry.

VIII.   ACKNOLEDGEMENT

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