GENERAL INDUSTRIAL PROCESS OPTIMIZATION METHOD TO LEVERAGE MACHINE LEARNING APPLIED TO INJECTION MOLDING

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T:he development of machine learning technologies are broadly changing how humans interact with their environments across all sectors. In industrial settings, this is referred to as the fourth industrial revolution, Industry 4.0, and encompasses several technologies that are pushing the boundaries of industrial automation. In this study, a general industrial process optimization (GIPO) methodology is formulated in the context of Industry 4.0 and tested on an industrial Injection Molding Machine (IMM). GIPO aims to encourage the practical inclusion of industrial artificial intelligence at all levels of the manufacturing process while enabling industrial equipment to adapt to a changing processing environment. Special attention is given to the generality of the methodology so that it can be extended to other applications. In the example case study presented here, GIPO combines nearest neighbors classification and nearest neighbors optimization methods to effectively optimize an Injection molding process. Practical implementation conducted on the IMM demonstrates a novel methodology to leverage data mining and machine learning methods in a real-world setting to improve the overall performance regarding production time, energy cost, and production quality.

Keywords: Industry 4.0, Injection Molding, Process Control Optimization, Industrial Machine Learning

Introduction

The term Industry 4.0 (I4) describes a growing collection of technologies available for factories to improve process performance. The combination of these technologies is revolutionary in terms of moving the manufacturing industry into the next generation of functionality. Combining data mining, machine learning methodologies, smart sensors, and a new generation of connected automation tools, has made smart systems the modern factory standard. Industrial equipment is broadly being fitted with smart sensors and integration of intelligent automation routines is becoming increasingly common. To maximize the effectiveness of these systems, all of the components of a smart process must integrate fluidly. In this study plastic injection molding (PIM) serves as a benchmark industrial process for the development of a general industrial process optimization (GIPO) methodology because of its complexity and prominence in the manufacturing industry. There has been significant development in recent years in terms of intelligent manufacturing in PIM, a process where the molten polymer is pushed into a mold and allowed to cool. The production quality of the plastic parts achieved through injection molding depends greatly on multiple highly coupled process variables that are difficult to measure and control [1].

One avenue of leveraging machine learning to improve the efficiency of the the PIM process is a quality prediction of the produced part. In their work, Jung et al. highlighted the use of autoencoders to capture the driving features in prediction quality [2]. Quality prediction is one part of the solution to improving the overall process, but it is necessary to consider the optimization of the production parameters. Some researchers have turned to knowledge-based systems to improve the overall process parameters [3]. Others have contributed with methods to reduce the dependencies of modeling actives on data such as Locker & Hopmann, who made use of transfer learning for process modeling [4]. The standard approach for improving overall PIM production is to optimize the predicted output of a given set of parameters using a model [5, 6, 7]. One notable characteristic of the PIM process however is that the dynamics of the many coupled process variables operate at different time scales. The time required to heat a metal mold is significantly more than the time required to harden molten plastic and produce a part. As such, converging to an optimal set of process parameters for an entire production line is limiting, in other words, optimal process parameters are not constant. The GIPO structure formulated here aims to help address this while contributing to the growing body of intelligent manufacturing literature and practical application examples.

In addition to the above, it is important to consider the challenges and opportunities that exist in transitioning through I4 [8]. Several studies have highlighted the necessity of standardization of intelligent system approaches for ease of integration of new technologies and availability are some of the challenges that need to be addressed for industry to move into the next generation of advanced automation [9, 10, 11]. The development and testing of methods to adapt industrial machinery to highly dynamic and complex manufacturing environments are necessary for the global manufacturing community to converge on a set of best practices and standard approaches [12]. This is especially true when considering machine-to-machine communication and operation, where different types of machines share information to optimize a factory-level process.

To this end, GIPO is formulated here and presents a generic procedure for including machine learning and data mining methods in different types of industrial processes. The GIPO approach is formulated and tested using an PIM to improve process performance for target production goals: (1) quality of production, (2) production time, and (3) energy consumption. These production goals are chosen as their optimization is expected to result in a more environmentally responsible and profitable process.

Plastic Injection Molding Process

IM production can be considered as a combination of sub-processes that can be divided into three categories: (1) plastication, (2) injection, and (3) cooling. These will be discussed in terms of how they contribute to final part quality and overall process performance. It is important to understand how the PIM sub-processes affect each other as the main contribution of GIPO is the codification of these highly dynamic and interactive processes in order to adapt to the changing processing environment.

Plastication

The production of a single part begins with plastication. During plastication, a rotating screw inside a heated barrel draws polymer pellets into the barrel where they begin to melt as a result of shearing forces and applied heat energy. This rotating action moves the polymer to the front of the screw while the screw is allowed to move backward under a controlled back pressure. During injection, the polymer melt that is at the front of the screw will be pushed into the mold. The final quality of the part will be dependent on several factors that have already come into play at this point in the production of a single part. These include, material temperature, and the pressure that the material is subject to during the plastication phase. Knowledge of the material composition and control of plastication pressure and speed, can be used to mitigate production problems [13]. This is especially true when considering the entire IMP which is made up of many measurable states such as mold temperature or material composition.

Injection

The injection phase of the PIM process consists of filling the mold with polymer, packing the polymer melt into the mold, and holding the polymer in the mold until the gate has frozen. The gate is the orifice through which the polymer enters the mold cavity. It is the smallest cross-section of the ejected part and is expected to harden first. The injection phase of part production is directly tied to the pressure inside the mold. It is well accepted that a consistent and desirable cavity pressure profile will result in consistent quality part production . Cavity pressure is considered the main measurable parameter to predict the part outcome, injection speed and mold temperature are production parameters that can be used to affect cavity pressure [17, 18, 19].

There are many challenges to controlling cavity pressure: (1) the filling and packing phase that is responsible for the rise to peak pressure happens quickly, (2) the control ability of the pressure profile is sensitive to the states of the mold and the material, and (3) it is often expensive and impractical to have pressure sensors in an injection mold. In this research, the conditions that exist in the mold are inferred based on observable outcomes over several cycles.

Cooling

Once the gate has frozen, cooling has begun. This is the last opportunity during the cycle to affect the production outcome. As the polymer solidifies in the mold, internal stresses must be allowed to dissipate to avoid undesirable mechanical properties of the part such as warping. The main control variables in the cooling process are coolant flow rates and temperatures [14]. Several methods have been used to improve the consistency and distribution of cooling such as predictive models, conformal cooling, and pulse cooling [15, 20, 21]. The main challenges to consider for the cooling phase of a cycle are cooling limitations due to part geometry and inconsistency of overall mold temperature. Cooling is the longest phase of the PIM cycle and is often the subject of cycle time reduction tactics.

General Industrial Process Optimization Structure

The study presented here aims to formulate a practical implementation of an adaptive process optimization routine. The methodologies used to achieve the base implementation of GIPO on the PIM are elementary, the focus of the study is the architecture used to leverage machine learning and optimization into a dynamic complex process. The GIPO approach considers a manufacturing process where a task or several tasks are repeated, with each repetition treated as a cycle. The example scenario presented in this case is a PIM, but the concepts described here apply to a wider range of applications. The following is a generic description of the GIPO methodology presented in the flow chart in Fig. 1 with components described in greater detail here.

Plant and System Controllers

In the context of GIPO, a plant is made up of one or more physical production components, such as machinery or processes that produce process variables. In the case of PIM, the plant is a combination of the injection molding machine and the mold chilling machinery. Process variables include: (1) any sensor or transducer measurement that can be digitally processed such as thermocouples, encoders, or current sensors, (2) variables that may not be measured, and (3) control variables such as speed, temperature, and pressure setpoints. GIPO achieves desired improvement goals by modulating process set points at a process cycle rate based on measured values that directly or indirectly affect the production process outcome.

Data Filters

Machine data produced in an industrial setting is typically large in volume, high in velocity, and subject to noise. Pre-processing can be used to reduce the dimension of the collected data as well as to appropriately remove noise. A data filter should codify tacit knowledge of a human operator, deciding what combinations of sensors and past decisions are important in achieving the end goal of improving the production process outcome. In this implementation of GIPO knowledge and experience of the manufacturing process was used to design an effective data filter. In this study, operations within the data filter limit consideration to key sensor measurements and a smart sensor, the Eigen Smart Module (ESM). The ESM translates thermal images into quality measurements. This greatly condenses the produced machine data into a pragmatic cycle datasets that can be compared against a larger process datasets. This is discussed in more detail in section . The cycle data, considered to be an instance is fed into a classifier that contains the process dataset. This is the Industrial Artificial Intelligence (IAI) engine 1 from Fig. 1. The process dataset that is contained in the IAI Engine 1 is the driving hypothesis space, **H**, of the GIPO methodology.

IAI Engine N - Setpoint Selector

The flow chart presented in Fig. 1 is a small-scale formulation of GIPO that is concentrated on one production unit, for example, one PIM cycle. Since a single production unit is considered in this formulation, the IAI engine N is labeled 1, $N = 1$. The purpose of GIPO Engine 1 is to select the optimal set of setpoints from **H** that is safe and achievable for the next production cycle. The target optimization goal should be determined based on plant requirements. Examples of target process optimization goals include quality, energy management, tool ware mitigation, cycle time, or a weighted combination of these. The following constraints for Engine 1 must be considered: (1) the change in setpoint from one cycle to another should be limited, and (2) processing time for solving the objective must be done between cycles and should be kept to a minimum. The suggested format for GIPO is as follows.

$$\mathbf{S} = \mathbf{H_{max}}\{\alpha_{\mathbf{\Lambda}}\mathbf{\Lambda} + \alpha_{\mathbf{1}}\mathbf{P_1} + \alpha_{\mathbf{2}}\mathbf{P_2} + \cdots + \mathbf{P_n}\alpha_{\mathbf{n}}\} \tag{1}$$

Where **S** is the list of optimal process set points, **H** is a hypothesis space, $\mathbf{\Lambda}$ is a likeness measurement, $\mathbf{P_n}$ performance measurement such as product quality and α_n

are corresponding weighting factors. The hypothesis space follows the format:

$$\begin{bmatrix} \mathbf{A_{1,(i-n)}} & \cdots & \mathbf{A_{1,(i-2)}} & \mathbf{A_{1,(i-1)}} & \mathbf{A_{1,(i)}} & \mathbf{A_{1,(i+1)}} \\ \mathbf{A_{2,(i-n)}} & \cdots & \mathbf{A_{2,(i-2)}} & \mathbf{A_{2,(i-1)}} & \mathbf{A_{2,(i)}} & \mathbf{A_{2,(i+1)}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \mathbf{A_{m,(i-n)}} & \cdots & \mathbf{A_{(m,i-2)}} & \mathbf{A_{m,(i-1)}} & \mathbf{A_{m,(i)}} & \mathbf{A_{m,(i+1)}} \end{bmatrix} \tag{2}$$

Where **A** is a set of attributes that describes the operating conditions of a cycle, including setpoints for process parameters. The variable i is the most recent production cycle, and n is the number of previous cycles considered to affect the outcome of the current cycle. The number of instances that are included in a **H** is m. Only instances with successful outcomes are considered in **H**

Every time a cycle finishes, the attributes of the most recent cycle and n previous cycles are compared with the instances in **H** to determine a likeness score $\mathbf{\Lambda}$. This is similar to a K-nearest neighbor classifier algorithm. The $\mathbf{\Lambda}$ is calculated using a percent difference between each attribute and then using a mean squared error to generate a single number for each instance in **H**.

$$\mathbf{\Lambda}_m = \sqrt{\sum_{i-n}^{i} (2[\frac{|a_{i,j} - a_{m,i,j}|}{a_{i,j} + a_{m,i,j}}]100)^2} \tag{3}$$

Where $_j$ in the term $a_{m,i,j}$ represents the iteration within the attribute list $A_{m,i}$ from equation 2. At the end of every cycle after the likeness, a score is obtained an optimal point is selected from **H** using equation 1. When the $\mathbf{\Lambda}$ is heavily weighted α_Λ compared to other weights α_n progression from one operating state to another will be slow. In some, cases this is desirable otherwise the weight $\alpha_{\mathbf{\Lambda}}$ can be adjusted accordingly.

IAI Main Engine Updater

The main IAI engine in the GIPO methodology is responsible for maintaining the **H** for GIPO Engines N. As new instances are created, they may be added to the **H** based on criteria set in the main IAI Engine. These updates can be made outside of the cycle loop, which allows more intensive data mining and machine learning operations to occur. Additionally, this distributed format allows the separation of knowledge. For example, the main engine may contain data for multiple mold configurations of an PIM, but the IAI engine N is only fed knowledge about the current mold that is used. This structure allows for a limitation to the size of the hypothesis space which may be desirable to ensure timely processing for any IAI Engine N optimization routine.

The separation of the cycle to the cycle variables (pressures and temperatures), and other process variables (material distributor and manufacture part) mitigates the curse of dimensionality by providing a real-time setpoint selection methodology. IAI Engine 1 can use an elementary classification routine while a more complex process optimization routine at the IAI Main Engine level can be leveraged. New data is continuously introduced in the IAI Main Engine, but the machine data will be repetitive and may not represent the full scope of possible outcomes to include in the **H**. This would equate to lost opportunities for improved process performance. A closer inspection of the IAI engine classifier routine will show the methodology resembles a standard nearest neighborsrs optimization routine, in that context, there is a danger that the algorithm finds a local minimum and remains in a sub-optimal operation region. When considering that GIPO is emulating a human operator, this would equate to an experienced operator being reluctant to try a new set of operating conditions on a piece of machinery.

The creation of waypoints is an important tactic that must be considered to ensure proper perturbation of the process and allow continued exploration of the process variable space during operation. Waypoints are false instances that are fabricated based on the belief that a better operating condition, than those examples provided, in the **H** exists. These points can be created in several ways, randomly, by an experienced operator or by an artificial intelligent inference routine. For the example presented in this paper, waypoints are created by a slight perturbation of existing operating points. This ensures better variance in the **H**. The fabricated points should be weighted heavily in equation 1 to ensure that they will be tested. In the presented example, this is done by assigning the points with high performances scores.

Example Applications

An industrial IMM was used to develop and test the GIPO platform. The details of the experimental setup and the algorithms used to achieve an implementation of GIPO are discussed below.

Experimental Setup

A 150-ton Engel IMM was instrumented with many sensors. Those used in this study are, Coolant Temperature Into Mold, Coolant Temperature Out of Mold, Coolant Flow Rate, Injection Speed, Screw Position, Hydraulic Back Pressure, Barrel Temperatures, Barrel Pressures, Current Sensors, and an Eigen Smart Module (ESM). Lab Windows and LabJack data acquisition hardware were used in conjunction with an ESM to collect data from the IMM and store it for data mining and processing. A Human Machine Interface was created using PyQtGraph, PyDaQmx, and other standard Python libraries to interface with the IMM. The IMM used in this study was uniquely suited for the development and testing of the GIPO algorithm. In addition to a large number of sensors the open architecture of the IMM control structure allowed for the implementation of control algorithms to automate the injection pack, hold, and cooling phases of the PIM. Model Predictive Controllers were implemented for applicable control valves.

Data Filters

Standard soft filtering techniques to correct noisy signals and DC offsets were used. In the case of the IMM, new data generated is considered at the end of every cycle, this is the cycle dataset. The data generated is formatted to match the attribute list of a (**H**) that has been created previously. For this implementation of GIPO, the attribute and target list can be found in Table . It is widely accepted that pressure and temperature sensor data are excellent indicators of PIM process. These are not easy to control directly and are often impractical to obtain. For this reason, they are not included in the attribute list. When formatting the data at the end of an injection cycle and to match the hypothesis space attributes, one previous part was considered from equation 2.

IAI Engine N Implementation

Initial Hypothesis Space

To initiate the process, a **H** was created by producing 100 parts with random process setpoints within the values indicated in Table . This initial dataset represents the baseline of the production process, in other words, this dataset represents the process without a GIPO implementation. The data was formatted offline to include the attributes listed in Table for 3 concurrent parts. These attributes were selected because they are key variables in describing the state of the process for any given cycle. All instances that resulted in a third party having poor quality were removed from the **H**, meaning that the **H**, only contains sequences of instances that result in successful production. The activity of managing the data to create meaningful **H** is left to the main IAI after this initialization. The resulting target variable scores achieved in the initial **H** are shown in Fig 2. The process production parameters targeted for process optimization are the energy index C_i, quality index Q_i, and the cycle time t_c. These are selected as they are common production performance measures in the injection molding industry.

Cycle time is the addition of cooling time, packing time, and holding time. The time required to inject the polymer into the mold is negligible in the context of cycle time. Injection speed is considered an important attribute in **H**. In this regard, injection time is inherently included in the optimization routine of GIPO. The C_i is the addition of the current drawn at each sampling instant over a cycle and then normalized. The quality score is a label that is returned by the ESM as good-part, short shot or flashes with a certainty p associated with it. The label is given a value of 1, 2, or 3 respectively and the value $p/2$ is added to that number to give each part a quality score. The Q_i is the addition of the current part quality score and two previous part quality scores. The initial **H** contains instances with attribute information and target information that is used to optimize the PIM with intelligent setpoint selection

Setpoint Selection

When the mold opens and a part is ejected, the IAI Engine N algorithm is activated. The most recent part cycle data is collected and formatted by the data filter and compared to each instance in the **H**. All of the instances are given a score using equation 1. The instance with the highest score is selected, in this way the IAI Engine N provides a set of setpoints that are used to produce the next part. After producing the initial **H**, a production run with the IAI alpha parameters $\alpha_{\mathbf{\Lambda}}$, α_1, and α_2 equaling 0.01, 10, 0.01 respectively was run. The values selected for the α parameters in this initial study are estimated to evenly distribute the weight of the importance associated with the target variable and es, and a full parametric analysis is saved for future study. Performance parameter data was extracted from the new dataset collected by the IAI main engine and is shown as hypothesis space 2 in Fig. 3. Next, the process was repeated changing the alpha parameter to $\alpha_{\mathbf{\Lambda}} = 0.01$, $\alpha_1 = 1$, and $\alpha_2 = 0.01$, This distribution of weights is selected to favor a reduction in cycle time which is evidenced by the resulting hypothesis space 3 in Fig. 3.

IAI Main Engine - Implementation

Setpoints that were included in the original **H** were available for the test resulting in the creation of hypothesis space 2 and hypothesis space 3. The advantage of limiting GIPO Engine N to a set of setpoints that have previously produced quality parts is the inherent safety of ensuring that only desirable process conditions are available to the process. The drawback to this is that optimal and safe process parameters can be overlooked. A suggested methodology to improve the variance of the **H** while mitigating risk is to vary available process parameters in a small incremental fashion. In the case of the IMM, this was done by perturbation of the original waypointss by a small amount from the real data points to create new synthetic points. A Bayesian classifier was trained using the original **H**, and the trained classifier was used to classify the quality score of the perturbed hypothesis space. The successful instances were added to the original **H** and are called waypoints. Figs. 4 and 5 show the results of how the perturbation added variance in the availability of key process setpoints. These were not tested on the actual injection molding machine for safety reasons. The investigation of fabricating waypoints lends itself well to future study in a virtual environment.

Summary of Results

During the production of parts for all hypothesis spaces, the PIM was challenged. The coolant temperature was set to 14 deg C and was allowed to cycle between temperatures of 10 deg C to 18 deg C. While these conditions are severe and practically unrealistic, they provide a significant disturbance to the system and challenge GIPO's capacity to affect the overall process performance. Conceptually, GIPO is successful if it can improve the production output under these conditions. The key performance results that were measured for the experiments are tabulated in Table . The creation of the first hypothesis space with random setpoints resulted in the "No GIPO" scores.

GIPO Test 1 is the result of implementing GIPO with the initial hypothesis space and values for $\alpha_{\mathbf{\Lambda}}$, α_1, and α_2 of 0.01, 10, and 0.01 respectively. These values provide evenly weighted performance criteria. GIPO Test 2 used the values $\alpha_{\mathbf{\Lambda=0.01}}$, $\alpha_1 = 1$, and $\alpha_2 = 0.01$ for set-point selection which weights cycle time heavily.

Discussions and Future Research

The GIPO approach formulated here is meant to help ease the pragmatic incorporation of I4 technologies, such as data mining and machine learning, into complex manufacturing systems to improve an overall process. The work presented is an introduction to the GIPO methodology. The initial formulation of GIPO has produced many opportunities for future research in terms of parametric studies, intelligent optimization routines with the study of waypoints, comparative studies of different machine learning and data mining methodologies, and case studies using different manufacturing processes.

The purpose of this initial formulation study was the incorporation of the algorithm into the PIM and demonstration the functionality of the methodology. The tools required to properly automate an intelligent autonomous system are broad and exist across several scientific research fields. Some key areas of improvement and future research are identified concerning each of the three main components of GIPO below.

Data Filters

When considering large amounts of data, there are several filtering, data-mining, and data pre-processing techniques available for the preparation of datasets. The translation of industrial big data into a workable data set is an active research topic in the field of data science. In practical applications, many sensors are subjected to noise. Adaptive filtering is one tactic to remove the noise that would be difficult to process for many artificial intelligence algorithms. This is also true for missing data or false data. In these scenarios, first-principle models and predictors can be used to validate, repair or infer data online [22].

IAI Engine 1 - Setpoint Selector

The optimization routine used in this study is strongly based on a K-nearest neighbors algorithm. Several other optimization tactics are well developed and appropriate for the GIPO platform. The performance of variations of GIPO resulting from using different optimization approaches is identified as an area of interest for future study. Examples of algorithms that could be considered to this end include fuzzy networks, genetic algorithms, and a host of offline search methods to name a few. Each of these algorithms has characteristics associated with them that would likely make them well suited for different applications.

IAI Main Engine - Implementation

In the case presented here, GIPO is limited to one machine. The overall process is relatively small in the context of a connected manufacturing plant. The main intelligent routine driving the evolution of the $\mathbf{H}$, retained successful operating points. The points were classified using data from an ESM. Some initial context on this can be found in [16]. The methodology of updating and adding waypoints can be enhanced using machine learning methods. The advantages of pattern recognition and inference models could be expected to significantly improve the capacity of GIPO to identify optimal settings for process control. Especially, when considering large plants that are likely very complex. This is saved for future study.

GIPO Scalability

In the example presented here, GIPO is a distributed intelligence over two engines. Where one engine populates the hypothesis space of an operating engine, GIPO Engine N. This structure can be adapted so that a GIPO main engine is used to populate and update the **H** of several GIPO Engines. An example flow chart depicting this structure can be found in Fig. 6. This structure allows the inclusion of complex dynamics in a supervisory sense while excluding complex models at the operating level of a plant. The purpose of this structure is to create a workflow for machinery where different components can collaborate effectively. The simulation and implementation of large GIPO platforms is another area of research yet to be conducted.

Conclusion

As intelligent systems become the new factory standard, it is necessary to develop methodologies for the pragmatic inclusion of new technologies offered by I4. To achieve this, multiple intelligent system approaches need to be considered and tested until the manufacturing community converges on a set of standards and best practices. The study presented here is a formulation of an intelligent system methodology tested on an PIM. Production tests show the functionality of the introduced GIPO architecture and help define the shape of future research that can be done to validate and expand on the basic GIPO structure. The fourth industrial revolution is disrupting the traditional manufacturing world, as a research community it is our responsibility to usher in this new age of intelligent manufacturing through experimentation and discovery. The formulation of GIPO aims to contribute to this end.

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Bibliography

[1] Zhao, P., Zhang, J., Dong, Z., Huang, J., Zhou, H., Fu, J., & Turng, L. S. (2020). Intelligent injection molding on sensing, optimization, and control. *Advances in Polymer Technology*, 2020.

[2] Jung, H., Jeon, J., Choi, D., & Park, J. Y. (2021). Application of machine learning techniques in injection molding quality prediction: Implications on sustainable manufacturing industry. *Sustainabilit*y, 13(8), 4120.

[3] Khosravani, M. R., Nasiri, S., & Reinicke, T. (2022). Intelligent knowledge-based system to improve injection molding process. *Journal of industrial information Integration*, 25, 100275.

[4] Lockner, Y., & Hopmann, C. (2021). Induced network-based transfer learning in injection molding for process modelling and optimization with artificial neural networks.*The International Journal of Advanced Manufacturing Technology*, 112(11), 3501-3513.

[5] Kitayama, S., Miyakawa, H., Takano, M., & Aiba, S. (2017). Multi-objective optimization of injection molding process parameters for short cycle time and warpage reduction using the conformal cooling channel. *The International Journal of Advanced Manufacturing Technology*, 88(5-8), 1735-1744.

[6] Bensing, R.J., Machavaram, R., Boopathy, S.R., & Jebaraj, C.(2019). Injection molding process optimization of a bi-aspheric lens using hybrid artificial neural networks (ANNs) and particle swarm optimization (PSO).*Measurement*, 134, 359-374.

[7] Fernandes, C., Pontes, A.J., Viana, J.C., & Gaspar-Cunha, A. (2018). Modeling and Optimization of the Injection-Molding Process: A Review.*Advances in Polymer Technology*, 37(2), 429-449.

[8] Müller, J.M., Kiel, D., & Voigt, K.-I. (2018). What Drives the Implementation of Industry 4.0? The Role of Opportunities and Challenges in the Context of Sustainability.*Sustainability*, 10(1), 247-271.

[9] Pivoto, D., GS, Almeida, L., FF, Rosa Righi, R., Rodrigues, J.J.P.C., Lugli, A.B., & Alberti, A. M.(2021). Cyber-physical systems architectures for the industrial internet of things applications in Industry 4.0: A literature review. *Journal of Manufacturing Systems*,176–192

[10] Stephan W., Mathias S., Moritz O., & Dominic G. 2015. Towards Industry 4.0 - Standardization is the crucial challenge for highly modular, multi-vendor production systems. *IFAC*, 579-584.

[11] Ahmadi, A., Cherifi, C., Cheutet, V., & Ouzrout, Y. (2017). A review of CPS 5 components architecture for manufacturing based on standards. *2017 11th International Conference on Software, Knowledge, Information Management and Applications (SKIMA)*, 1-6.

[12] Trappey AJ., Trappey CV., Govindarajan UH., Chuang AC., Sun JJ. (2017). A review of essential standards and patent landscapes for the Internet of Things: A key enabler for Industry 4.0. *Advanced Engineering Informatics*,1(33),208-29.

[13] Ruan, Y., Gao, H., & Li, D. (2019). Improving the Consistency of Injection Molding Products by Intelligent Temperature Compensation Control.*Advances in Polymer Technology*, 2019, Article ID 1591204.

[14] Zhang, S. Dubay, R. & Charest, M. (2015). A principal component analysis model-based predictive controller for controlling part warpage in plastic injection molding. *Systems with Applications*, 42(6), 2919-2927.

[15] Everett, S.E., & Dubay, R.(2017). A sub-space artificial neural network for mold cooling in injection molding.*Expert Systems with Applications*, 79, 358-371.

[16] Charest, M., Finn, R. & Dubay, R. (2018). Integration of artificial intelligence in an injection molding process for online process parameter adjustment. *2018 Annual IEEE International Systems Conference (SysCon)*, 1-6.

[17] Huang, M.-S. (2007). Cavity pressure-based grey prediction of the filling-to-packing switchover point for injection molding. *Journal of Materials Processing Technology*, 184(2), 419-424.

[18] Kurt, M., Saban K.O., Kaynak, Y., Atakok, G., & Girit, O. (2009). Experimental investigation of plastic injection molding: Assessment of the effects of cavity pressure and mold temperature on the quality of the final products. *Materials & Design*, 30(8), 3217-3224.

[19] Tsai, K.-M., & Lan, J.-K. (2015). Correlation between runner pressure and cavity pressure within injection mold. *The International Journal of Advanced Manufacturing Technology*, 79(1), 73-284.

[20] Chen, S.-C., Chang, Y., Chang, T.-H., & Chien, R.-D. (2008). Influence of using pulsed cooling for mold temperature control on microgroove duplication accuracy and warpage of the Blu-ray Disc.*International Communications in Heat and Mass Transfer*, 35(2), 130-138.

[21] Xu, X., Sachs, E. & Allen, S. (2001). The design of conformal cooling channels in injection molding tooling.*Polymer Engineering & Science*, 41(7), 1265-1279.

[22] Diez-Olivan, A., Del Ser, J., Galar, D., & Sierra, B. (2019). Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0.*Information Fusion*, 50, 92-111.

Tables

Table Attribute list

Atributes	Values	Units
Injection Setpoint	50-112	mm/s
Packing Setpoint	0-160	MPa
Holding Setpoint	0-160	MPa
Plasticate Setpoint	0-160	MPa
Cool Time Setpoint	5-20	seconds
Pack Time Setpoint	0-10	seconds
Hold Time Setpoint	0-10	seconds
Coolant Flow Rate Setpoint	0-30	L/min
Coolant Temperature (In-Out)	10-25	°C
Coolant Flow Rate	0-30	L/min
Injection Speed	0-112	mm/sec
Screw Position	21.6	cm
Hydraulic Back Pressure	0-160	MPA
Barrel Temperatures	200	°C
Barrel Pressure	0-20	MPA
Current Sensors	0-50	Amps
Eigen Smart Module (ESM)	Quality	Short Shot, % Good Part, % Flash, %

Table Results of Different GIPO weights for Performance criteria

Test Descriptor	Energy Score Average	Quality Score Average	Cycle Time Average
No GIPO	6.79	2.83	14.23
GIPO - Test1	5.21	3.10	16.58
GIPO - Test2	8.39	3.25	11.00

Figures

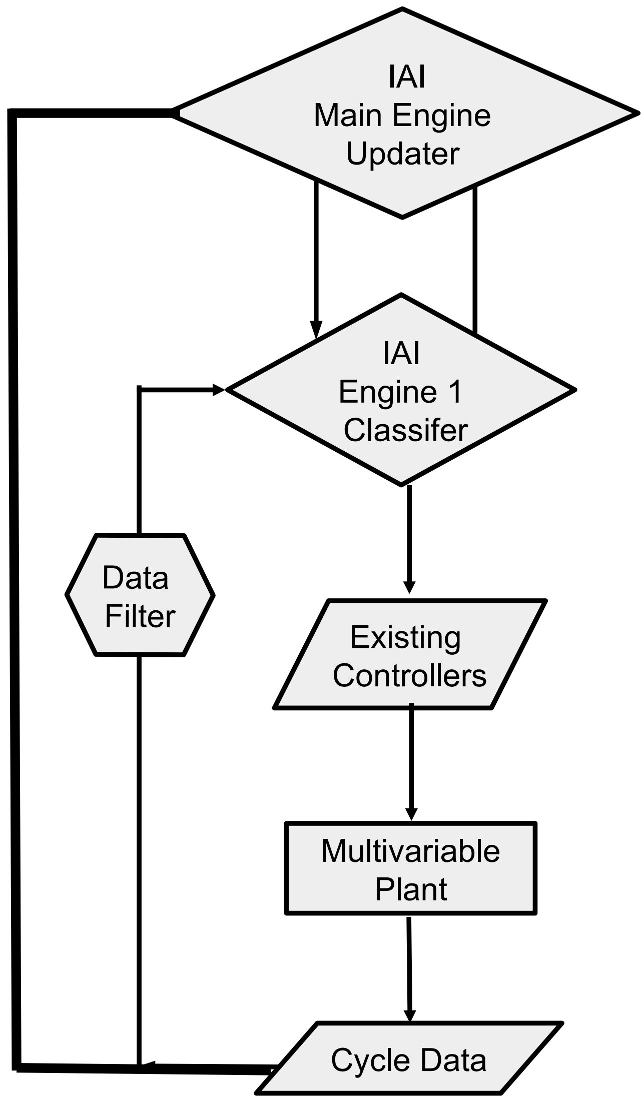

Figure 1: GIPO Flow Chart

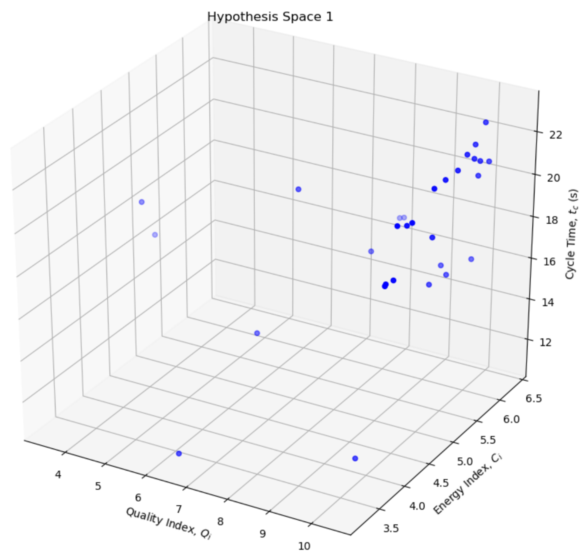

Figure 2: Way Points - Cycle Time Variables

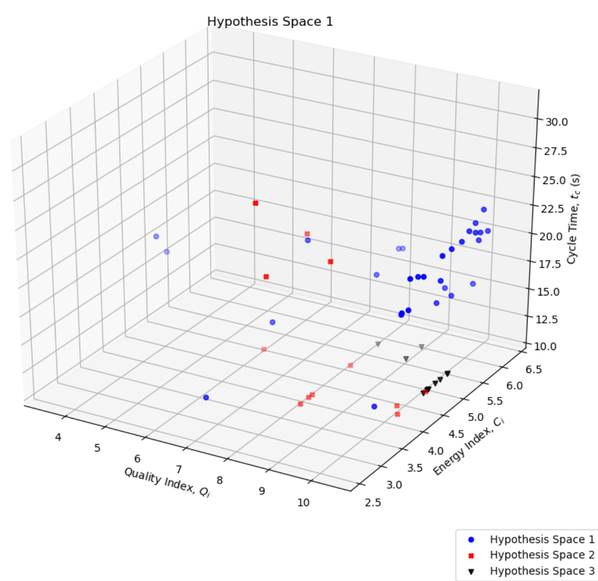

Figure 3: Hypothesis Space Visualization

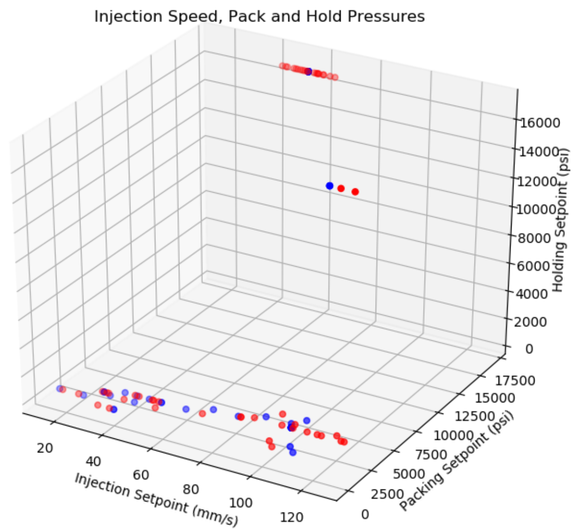

Figure 4: Way Points - Injection Variables

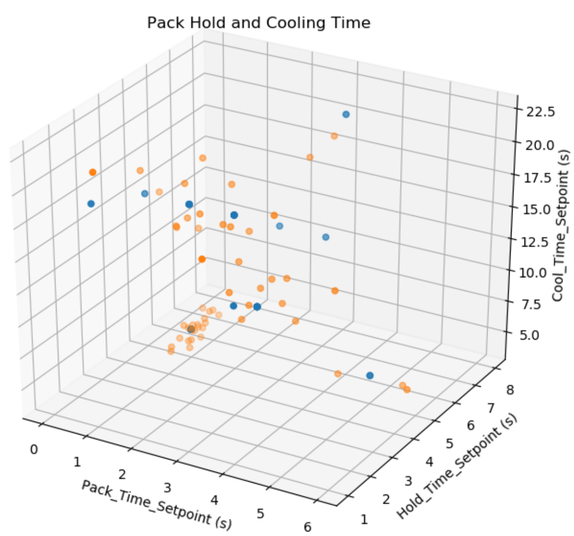

Figure 5: Way Points - Cycle Time Variables

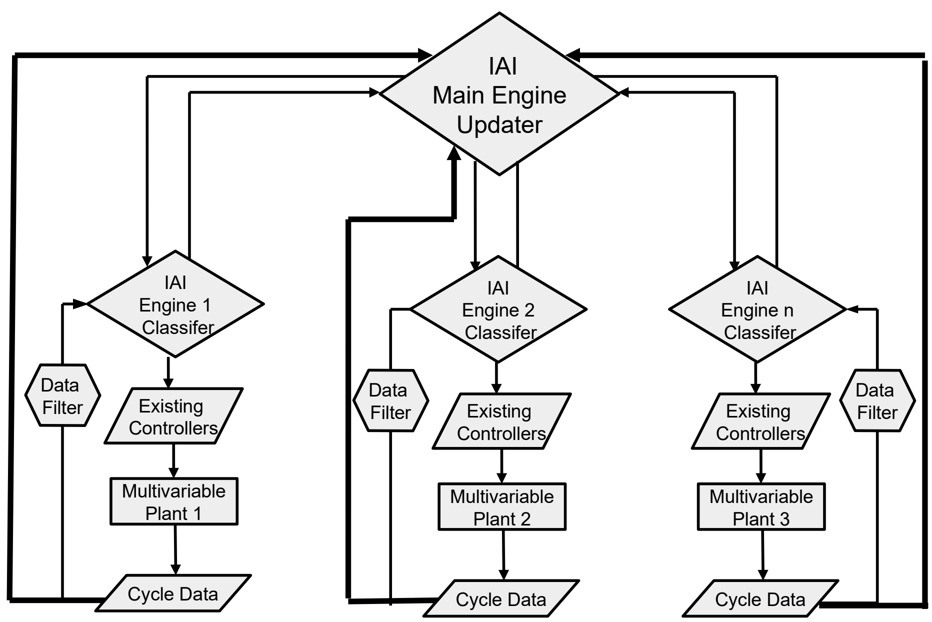

Figure 6: Way Points - Cycle Time Variables