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Initial Investigation of Online Control System for Selective Laser Melting Process: Multi-layer Level

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***Abstract*—Selective Laser Melting (SLM), an additive manufacturing process, has attracted significant attention from academia and industry over the past two decades. SLM is a productive technique for creating complex industrial components and tools with fewer stages, resulting in resource conservation in contrast to conventional manufacturing methods. Nonetheless, the current platforms employed in SLM metal part production lack the efficient utilisation of an online closed-loop system. The literature showed a significant place for utilising advanced control systems to improve overall performance. Such enhancement will enable the process to be used to fabricate more sophisticated parts. Introducing an online control system could also empower part production with better internal microstructure characteristics. This research reports an initial investigation of applying a closed-loop system to reduce the effect of heat accumulation while building a multi-layer object, thus improving the system. The controller changes the laser input in the track and considers the temperature residuals for the completed layers. The simulation results presented a significant improvement in disturbance rejection and better control of the melt-pool characteristics.**

***Index Terms*—Metal additive manufacturing, selective laser melting, laser powder bed fusion, feedback control, PID, mlti-layer.**

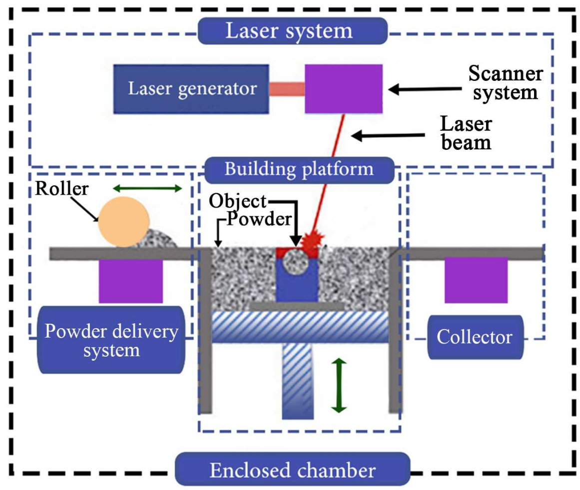

Fig. 1. The basic structure of SLM process

I. Introduction

Additive manufacturing (AM) is a group of manufacturing techniques to build 3D parts directly from a digital design. The building is achieved by printing one layer after another until the full product is completed [1]. The technology is a fast manufacturing tool since it reduces many traditional fabrication steps. It provides more flexibility and freedom in product design. These features made AM a competent option in many applications, such as construction, medical field, aerospace and much more [2]. AM technology can use various types of materials such as polymers, ceramics, and metals to fabricate the desired object [3]. The technology is divided into seven groups based on the heat source, the material that it can process, and the form of the material (wire, powder, and liquid): photopolymerisation, material jetting, binder jetting, material extrusion, sheet lamination, direct energy deposition (DED), powder bed fusion (PBF) [1].

One of the rising techniques is the selective laser melting (SLM) process, which is a laser PBF technology that uses a high density and narrow laser source to fuse the powder particle selectively [4]. SLM processes are capable to produce parts with high resolution, lightweight structure, and internal channels to enhance their mechanical properties [5]. The process consists of five primary parts, here is a brief description of each one:

1) Laser Unit: This part controls the laser beam power, speed, and scanning pattern across the building platform.
2) Powder Delivery system: The unit uniformly deposits and compresses the material powder to add a new layer.
3) Building Platform: This is where the object is fabricated. The platform lowers after each layer to add a new one.
4) Collector Unit: This unit collects excess powder.
5) Enclosed Chamber: A sealed space that regulates ambient conditions.

In addition to these components, an industrial machine may include a monitoring unit to control ambient temperature, machine characteristics, and part production. Figure (1) demonstrates the main units of the SLM process. The production process of the 3D object using SLM process involves several steps [6]. It starts with transforming the 3D model to a set of slices and stores it in an appropriate file format, such as an .STL file. Then the machine parameters are configured to prepare for the production. The manufacturing process constructs each layer on top of the previous one until the part is complete. Finally, the completed part is moved out from the building platform and cleaned.

Despite the significant advancements in metal Additive Manufacturing, there are still several challenges and limita-

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tions that hinder its ability to fully meet industrial requirements [7]. The AM process is influenced by numerous factors, making it difficult to guarantee consistent quality and repeatability [8]. In most existing processes, including SLM and other AM techniques, process parameters remain constant throughout the printing process [9]–[11]. These parameters are typically selected through trial and error or optimised with the help of expert knowledge and modeling/simulations [12]. However, relying on fixed parameters can cause issues like heat accumulation, leading to irregularities in the melting pool morphology, especially when dealing with complex geometries, resulting in various defects.

Through the past twenty years, extensive research efforts have been dedicated to improving part quality in metal AM. There is great emphasis in the literature on the importance of introducing an online control system to enhance the performance of the SLM process [8], [13], [14]. There have been multiple attempts in the literature to design control systems for the SLM process. The existing control efforts in the literature can be classified into two groups: in-layer and layer-to-layer control systems. The first type variates the control variables (laser parameters) continuously during the process, while the second updates the process parameters once every layer. The in-layer control strategy requires a rapid sensing and processing system to respond to any deviation in the process, which could be a practical limitation. However, achieving such a control system will guarantee the accuracy of the building. The existing efforts ignored the inherited heat from the printed layer. On the contrary, the layer-to-layer control system approaches update the control signal once every layer. Thus, it cannot handle the errors that occur during the layer.

This study aims to demonstrate the impact of using online feedback system for the SLM process while fabricating a multi-layer object. In other words, the controller will react to the changes occurring during the whole process in layer and while adding a new layer. The control system will regulate the geometry of the melt-pool and reduce heat accumulation during the process. Based on the best of the authors' knowledge, the absence of such investigation in the literature is a clear research gap that is an important step towards automating the SLM process.

In the upcoming sections of the paper, will cover the following topics. Firstly, Section II, will provide a quick survey of the control effort in the SLM process. After that, in Section III, the physics model that is used in this investigation will be presented. Subsequently, in Section IV, the control problem and the control system design will be addesed. Section V will present and discuss the simulation results and highlight research opportunities in the online control system of the SLM process. Finally, Section VI, summarises the findings of the investigation and outline the future work.

II. Effort in online control system for SLM process

As highlighted in various academic works, the utilisation of an online control system offers a promising solution for addressing disruptions in the manufacturing process and mitigating the adverse effects of irregularities in the molten pool during the component fabrication procedure [13], [15]. Numerous control systems have been proposed and examined within the scholarly literature. In most of these research studies, special attention has been given to the geometry and thermodynamics of the molten pool as indicators of process quality [16], [17] . The regulation of the molten pool's geometry and temperature has been shown to yield improved microstructural characteristics and enhanced mechanical properties. The implementation of a control system serves to prevent issues such as porosity, distortion, cracking, as well as various manufacturing anomalies like keyhole formation and swelling.

Irrespective of the metric used to assess quality, both are intrinsically linked to the energy density allied in the process, which is a parameter that can be adjusted through manipulation of key variables such as laser power, scanning speed, and scanning strategies [18]. The existing effort in regulating the performance of the SLM process can be categorised generally into two groups: classical control and data-driven approaches. Proportional (P) and Proportional-Integral (PI) controllers were the first types of controller that have been investigated to improve the geometry of the produced part by the controller in the laser source power [19]–[21]. It is important to mention that the control system was designed on the basis of a second-order empirical model. The findings showed the potential effectiveness of an online control system in improving the overall quality of the process.

Years later, with the advent of new and advanced machines along with innovative process mechanisms, researchers were once again motivated to tackle the control challenges within the SLM process. Researchers in the studies [11], [22], utilized a Field-Programmable Gate Array board to develop an integrated control system that combined a P controller and a feedforward controller. The control structure was designed to regulate the temperature of the melt pool by controlling the laser power. The results showed a 73% reduction in temperature error compared to the open-loop response.However, it is worth noting that this study had limitations as it focused on a small number of well-separated multi-tracks.

In prior studies, the control systems relied on observations and empirical experimentation models. However, in [9], a feedforward (FF) controller was developed using a control-oriented model. The research findings demonstrated that this designed controller effectively maintained control over the melt-pool geometry throughout the process, resulting in a substantial 23% reduction in error when compared to operating with a constant laser power setting.

The use of data-driven techniques in the SLM process began with a preliminary investigation, as described in [23], [24]. This investigation introduced a model-free control system that utilised Iterative Learning Control (ILC) principles. The control system aimed to adjust the power input within the scanning segment based on real-time data from the monitoring system. In another study, a data-driven model was used to predict system performance and reduce the influence of temperature history [25].

In a recent study [17], the authors used deep learning and machine learning techniques to predict disturbances that may occur during a process within a specific area. The area of interest was defined by a cylinder that encompasses the environmental conditions around the operational point. The researchers formulated the system as an optimisation problem that can be solved using an ILC algorithm by analysing both past and current data. These research efforts demonstrated the viability of controlling the SLM process exclusively using real-time data. However, it's important to note that the proposed algorithm, which relies on repetitive behaviour, may not be suitable for geometrically complex components.

In [26]–[28], the authors built a controller based on a difference model. The first study proposed a batch model predictive control to the temperature of the melt pool. The controller can handle the repetitive and non-repetitive disturbance during the process. The second work utilised state-feedback control to regulate the thermal behaviour of the process. Whereas the two previous works were concerned about in-layer control, the third investigated the use of ILC to update the control signal every layer. The authors of this article investigated recently conducted research on the use of a fuzzy logic control (FLC) algorithm as a potential control method for the SLM process [29]. They developed a basic FLC to address the problem of heat buildup while printing a single layer of metal. The results demonstrated a substantial decrease in the error values. In summary, all the highlighted efforts tackle either in layer or layer-to-layer control problems. From the used model point of view, the models varied between: experimentally based, difference model, or physics-based model.

In this work we present simulation results of building 3D part under the use of PID controller to regulate the melt-pool area and, a specific novelty is the consideration of the heat accumulation from track to track and layer to layer.

III. Process model

The modeling and simulation of additive manufacturing processes are essential in accelerating the design and the production process by minimizing actual trials. Moreover, these fields help us to understand the underlying physics of the process and the impact of different process parameters. There are many modeling studies available in the scientific literature, but most of them concentrate on the impacts related to thermal dynamics in the melt pool [9]. This is because the temperature of the substrate during the process affects many properties. Models can be based on physics or data-driven approaches [30]. There are ODE, PDE, linear, nonlinear, and empirical models [31]. Within all of these existing and diverse models, unfortunately, there are very few models that describe the selective laser melting process and fewer which are control design oriented.

This research investigation used the model presented in [9]. It is a physics-based model that takes into consideration the material properties and process parameters. The model assumes that the laser path is a set of parallel tracks that move back and forth in every layer as shown in Figure (2). The model includes the effects of the completed tracks on the upcoming ones. The impact is considered as a disturbance to the process.

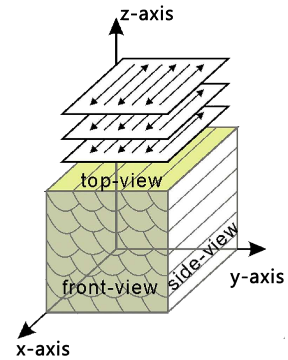

Fig. 2. The illustration of the printing process, layer by layer, back and forth in each layer

The model integrates the heat balance equation and the Rosenthal solution to calculate the melt-pool's cross-sectional area $A(t)$. The model starts from the energy balance equation that can be presented as follows:

$$\frac{d}{dt}(\rho V(t)e(t)) = -\rho A(t)v(t)e_b + P_s(t) \tag{1}$$

where ρ,e_b, $e(t)$, are the material density, the specific energy, and the specific internal energy. $P_s(t)$ and $V(t)$ present the power delivered and the melt-pool volume. Applying the set of assumptions related to the shape of the melt-pool, the temperature of the steady-state melt-pool, and the material properties that is described in more details in [9] Equation 1 can be rewritten as

$$\frac{dA(t)}{dt} = f(A(t), T_{init}) + g(A(t))Q(t) \tag{2}$$

where $T_{init}(t)$ is the initial temperature that can be give as

$$T_{init}(x,y,z) = T_a + \Sigma_{j=1}^{i-1}\frac{q_i}{2\pi k R_j}e^{-v_j(w_jR_j)/2a} \tag{3}$$

and $Q(t)$ is the laser input power. The parameters k, a in Equation 3 are the thermal conductivity constant and the thermal diffusivity of the material, respectively. The symbols q_i and $v(t)$ represent the virtual source power, which is the power at the return end of the track, and the scanning speed of the laser beam. Meanwhile, the symbols R_j and w_j denote the distance between the operation point and the virtual source, and the distance in the x-direction between the operation point and the virtual source. Here, i is the number of printed tracks. In this work the process parameters are selected to present what is actually used in practice. Furthermore, the Rosenthal solution presented in Equation 3 was applied to estimate the heat residual passed to the next layer. Despite the fact that the model was able to generally capture the behaviour of process, and the model is not yet verified with the given modification.

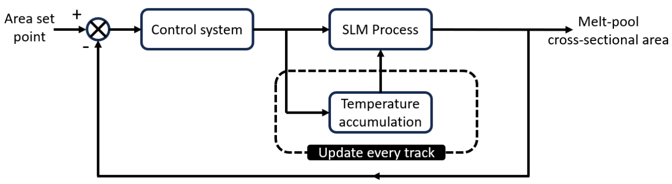

Fig. 3. Generic block diagram of control system implementation for the SLM process

IV. Controller Design

A. Problem statement

As noted in the earlier sections, heat accumulation poses a significant challenge that affects the quality of the resulting component. Consequently, the objective of the control system is to regulate the cross-sectional area of the melt pool A(t), by controlling the laser power input value Q(t), to minimise heat buildup. The control design is established with the assumption that all process settings remain constant and the only variable under control is the laser power level. Figure (3) illustrates the generic block diagram of the process with the feedback control system.

B. Controller design

The proportional-integral-derivative (PID) controller is the most used controller in the industry; almost 90% of used controllers in various industrial applications are based on PID [32]. It provides a simple yet efficient solution for the control problem. From its name, the PID control consists of the main parameters. The P term responds proportionally to the error signal, where the second integral part corrects the control signal based on integrating the error signal over time. The effect of an integral part appears in reducing the steady-state error. The derivative part is responsible of improving the transient response of the system based on the rate of change of the error signal.

The selection of the control variables are achieved through various tuning method varied in their simplicity, such as Ziegler-Nichols, Cohen-Coon, particle swarm optimisation or genetic algorithms, model predictive control and many more [33]. The method used depends on several factors, such as the nature of the process, the level of accuracy required, the accessibility of data, etc.

Since this work is more interested in providing evidence of the effect of PID control on the SLM process performance, $MATLAB$ auto-tuning toolbox was used to select the PID gains: proportional gain (k_p), integral gain (k_i), and derivative gain (k_d). The toolbox was fed with a linearised model of the process. The linearisation was done around the desired cross-sectional area with the crossponding initial temperature. The used PID structure can be described by the following equation:

$$u(t) = k_p e(t) + k_i \int edt + k\dot{e}(t) \tag{4}$$

Assuming there is a sensor that can provide the required data, a fast processer to handle them, and an actuator that respond fat to the changes ,the controller will provide continually the control signal $u(t)$ based on the calculated error value.

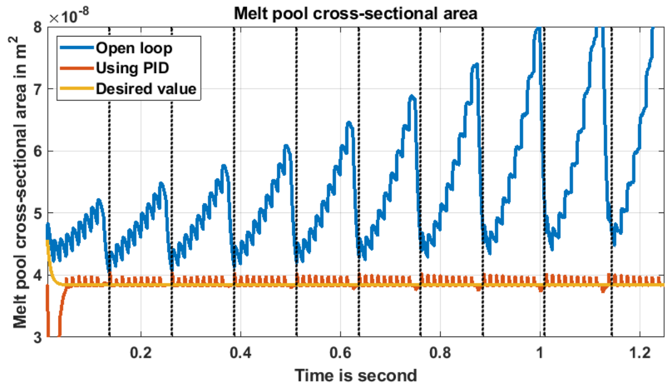

Fig. 4. The simulation result of the melt-pool cross-sectional area with and without a controller .

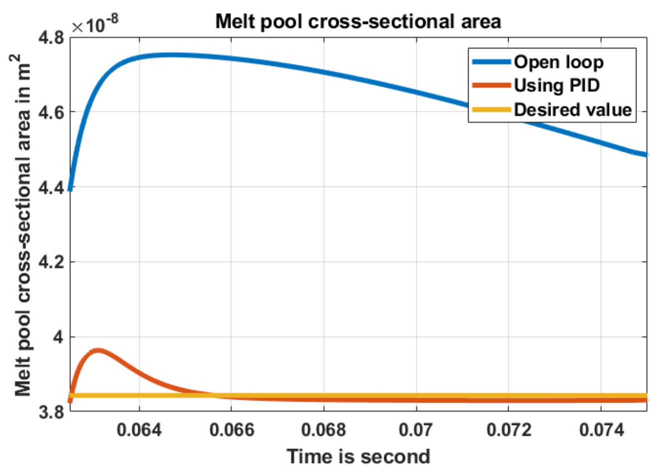

Fig. 5. The simulation result of the melt-pool cross-sectional area for a single track with and without a controller

V. Simulation and Discussion

The process model presented in the previous section III is used to simulate the behaviour of the melt pool while printing a part of ten layers that consists of ten tracks of length of 1 cm of Ti6Al4V powder. The reference value was selected to be 3.8e-8 mm^2. This value is computed using the model under perfect conditions and without heat accumulation. Figures (4-6) demonstrate the system response, the initial temperature, and melt-pool temperature during the process.

Figure (4) shows the cross-sectional area of the melt pool during the process. The black dotted line presents the start of a new layer. Looking into the system response without controller presented by the blue curve, the value of the cross-sectional area operates away from the desired size, and the deference becomes worse on every track. The drop at the start of each layer is due to the effects of adding a new layer. As it was explained in the previous sections, adding a new layer cools down the process, however there is still

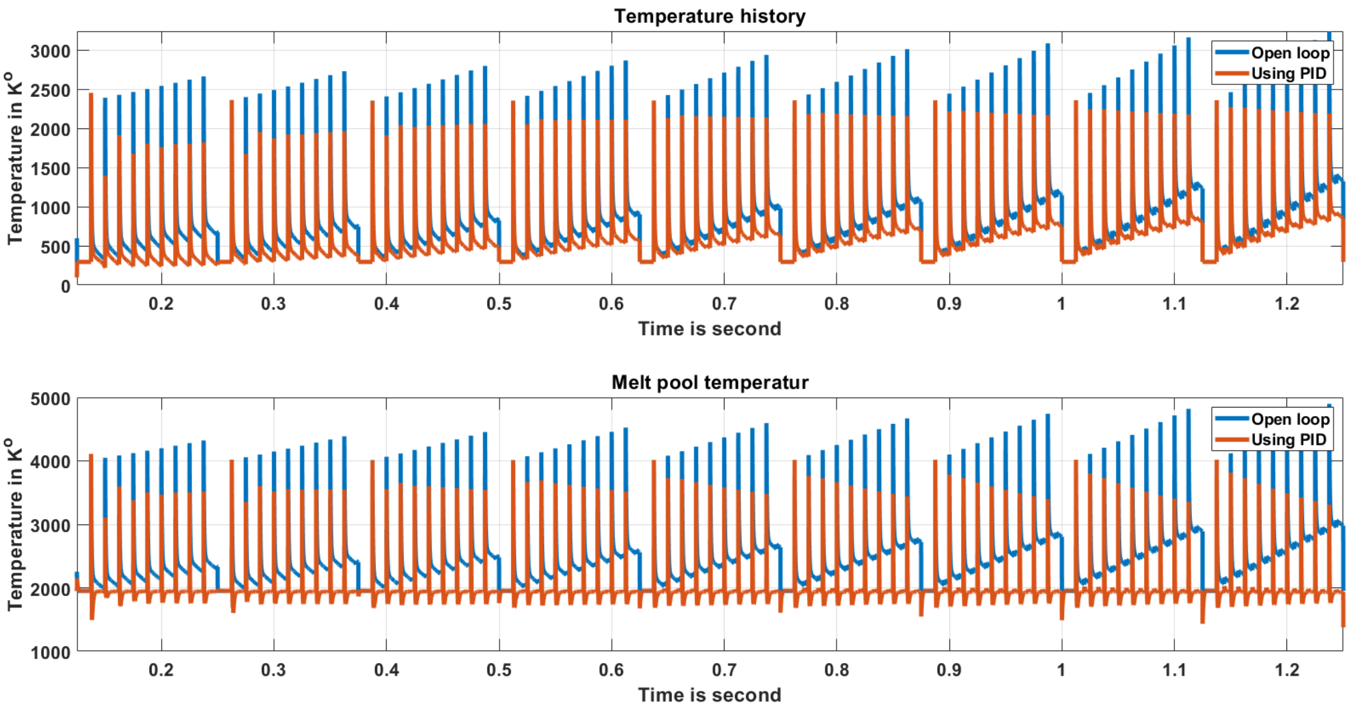

Fig. 6. The initial temperature and melt-pool temperature profile during the process simulation with and without a controller.

some temperature residual that is past from the completed layer to the new one. Introducing the control system resulted in an enhancement of the system's transient and steady-state responses, as demonstrated by the red curve.

Figure (5) demonstrate the huge difference between the open-loop and closed-loop performance during the simulation of one of the tracks. Looking into the initial temperature profile presented in the top plot in figure (6), it can be seen clearly the reduction of disturbance level. The controller helps to regulate the melt-pool temperature area. As it can be seen from the bottom plot in figure (6), the temperature keep operating around the melting point. Regulating the melt pool temperature during the printing process enhances the quality of the produced part as many of investigations indicates. [34]. Figure (7) presented the IEA and the average used power during the simulation. As it can be seen, that using controller reduce the IEA to more than 58 % and save around 18 % of power. Despite the promising potential demonstrated by the use of an online control system, further research is required in various areas. The following research opportunities have been identified during this study:

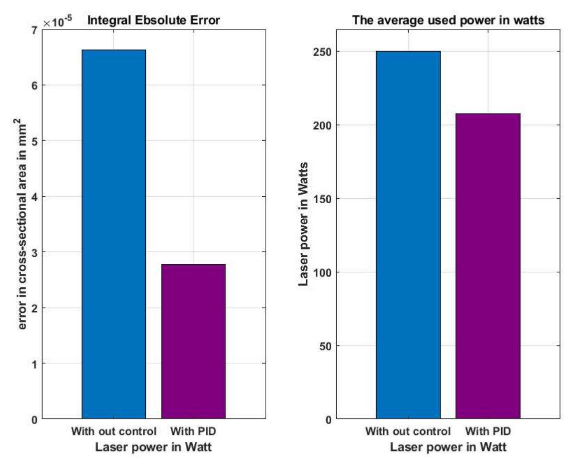

Fig. 7. A comparison between the open-loop and closed-loop performance in terms of IAE and average power consumption

1) Practical Validation: There is a need for practical validation of the model and control system performance. Current limitations exist when using Rosenthal solutions to represent heat accumulation, as it assumes that disturbances originate only from the end of each track. In practise, disturbances could arise from points before, the underlying layers, and/or the surrounding environment.
2) Complex Building Processes: Most studies, including this one, test control systems during simple printing or construction. Testing them in complex building processes is important to evaluate practical effectiveness.
3) Modern Tuning Methods: Investigating modern tuning methods, such as adaptive approaches, could enhance system performance, especially when dealing with complex shapes.
4) Accessible Equipment: SLM control algorithms need more accessible equipment for practical implementation due to manufacturer restrictions on sensor and actuator access.

VI. Conclusion

This research work presents preliminary findings regarding a common industrial online control strategy for the Selective Laser Melting (SLM) process. It reaffirms the observations made in previous studies about the substantial potential of online control to significantly enhance process behavior. This, in itself, should encourage equipment manufacturers to facilitate greater access to sensor and actuator architecture, enabling more comprehensive practical investigations. Furthermore, this study introduces a level of investigation that, up until now, has not been thoroughly explored in the literature. The analysis of a control system in a multi-layer process represents a notable research gap. Despite the accuracy of the used model, the initial investigation provides evidence of the effectiveness of the online control system in enhancing the performance of the SLM process. Certainly, this topic requires more research and development of systematic tuning rules to handle complex conditions that occur in SLM. Additionally, exploring advanced feedback control methods that utilise more sophisticated control theory and intelligent-based control methods would be beneficial. However, it is important to balance the need for simple systems that can be implemented in an industrial setting.

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