IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received November 7, 2016, accepted December 27, 2016, date of publication March 1, 2017, date of current version March 28, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2671864

Intelligent Computer-aided Process Planning of Multi-axis CNC Tapping Machine

CHIN-SHENG CHEN[1] AND YIN TUNG ALBERT SUN[2]
[1]Graduate Institute of Automation Technology, National Taipei University of Technology, Taipei 10608, Taiwan
[2]Graduate Institute of Manufacturing Technology, National Taipei University of Technology, Taipei 10608, Taiwan

Corresponding author: Y. T. A. Sun (ytsun@mail.ntut.edu.tw)

This work was supported by the Ministry of Science and Technology of Taiwan under Contract 105-2218-E-027-004 and Contract 105-2218-E-027-013.

ABSTRACT The increasing complexity of the manufacturing industry demands computer numerical control (CNC) machining, a massively used process that is equipped with an intelligent feature. Not only does its control function revitalize competition in a sustainable manufacturing ecosystem but also advances the Industry 4.0 readiness. This paper develops an intelligent computer-aided process planning (i-CAPP) based on two widely accepted performance measures: manufacturability and efficiency. Machine tapping is a very popular CNC machining process making threaded holes, from which there is an investigation of two manufacturability scenarios. The first scenario deals with all holes with the same size that undergo the same operation (OP). The second one handles the groups of holes with different sizes machined by various OPs. Meanwhile, the study of efficiency focuses on point-to-point drilling, tapping, and chamfering. This research work verifies such indicators by proposing hybrid-two-stage optimization algorithms: 1) traveling salesman problem and 2) innovative Tabu Search. The i-CAPP verification of both indicators was confirmed in an application with a five-axis CNC tapping machine to realize the Industry 4.0 readiness. Extensions of the research in the pursuit of higher intelligent manufacturing platforms are discussed.

INDEX TERMS Computer-aided process planning (CAPP), traveling salesman problem (TSP), tabu search (TS), multi-axial computer numerical control (CNC) machining, point-to-point (PTP) operational control, performance index.

I. INTRODUCTION

Process planning models to improve decision making and enhance knowledge management, research on Computer-aided Process Planning (CAPP) and Computer Numerical Control (CNC) are interdependently studied through machining-process-related parameters and variables. As a result, CNC capabilities for specific domain-knowledge areas become variables for the improvement of machining performance in industry. As examples, for more than two decades, generative CAPP-embedded CNC processes which include turning, cutting & abrasive, prismatic-feature machining and machine tool selection have been developed [1]–[4]. It is observed that CAPP, being an integral strategy, is customized to fit widely implemented CNC processes while some algorithmic approaches, which are associated with generating code for NCs or CNCs, are transferable among search reasoning engines and their interfaces. Khan *et al.* [5] used so-called Simulated Annealing (SA) algorithm to simulate non-productive motions such as the cutting tool entering and exiting by searching numerous endpoints that form certain geometries. An optimal searching algorithm is generated for sequencing the process operations for workpiece features [6]. Further relevant exploration focused on a three-tier system that combines CAD, CAPP and CNC interchangeable factors [7], [8]. These, however, are only suitable for a simulated environment where nominal or theoretical data dominate software calculation.

The other critical research and development (R&D) on CAD-CAPP-CNC verification and validation evaluates the calculated path planning with a realistic case. A straightforward point-to-point (PTP) based metaheuristic algorithm may be viewed as a variant CAPP with NC-driven laser cutting process implementations [9], [10]. Consequently, more tangible economic considerations become accountable, tractable and comparable for intelligent machining process assessments. Through system advancements, Tsai *et al.* [11] applied Genetic Algorithms (GA) for a discrete optimization on NC-driven drilling process for holes on integrated circuit (IC) boards. As for machining performance criteria, Lo [12] considered feed rate as an important index for machining efficiency and quality to overcome the limitation of a constant feed rate by using critical control points to interpolate and analyze curves and surfaces. To maintain machining accuracy requirement, Cho *et al.* [13] developed optimizing algorithm by reiterating paths in order to minimize travelled points with an implementation as a proof of concept. Pedagopu and Kumar [14] emphasized an intelligent CAPP as an integral part of modern manufacturing technology integration towards more transparent feedback and feedforward parameters and variables portrayed in so-called industry 4.0 paradigms. Jaider *et al.* [4] defined CAPP/CAM that should be domain-independent by considering downstream machining processes. However, algorithms developed by the previous researchers handled segregated machining processes, in terms of hole size, tool change and toolpath planning. This paper proposes a comprehensive approach to consider previously mentioned factors for the purpose of deepening manufacturability and efficiency into the Industry 4.0 readiness. That is, a series of PTP OPs enables end-to-end digitization of critical physical machining assets with intelligent integration of CNC practices. Tangible information and transparent communication facilitates internal and external manufacturing value stakeholders to take partnership to build and sustain vertical and horizontal value chains, which are compose of various value streams. Consequently, such a holistic CAM environment recognizes and integrates CAPP that is suitable for the aspects of the so-called fourth industrial revolution [15].

II. METHODOLOGY OF FEATURED INDUSTRY 4.0 COMPONENTS

In order to leverage as many perspectives as possible from peers who are involved in Industry 4.0 architecture, the literature review emphasizes how to revitalize traditional CAM systems with achievable extension in CAPP. According to a recent survey that tracked a trending paradigm advancement to address the Industry 4.0 readiness over ten years from 2003 to 2014, so-called agent-based manufacturing enterprises underwent three levels of reconfigurable manufacturing systems [16]. Furthermore, in terms of R&D tools, process planning related ones only account for about 3% (two out of 67) published cases. Moreover, it's worth noting that those identified are either in level one as a methodological framework, or in level two in hypothetically problem solving stage. Wu *et al.* [17] literature review of commercial software, drew a comparable conclusion about CAPP tools. Similarly, recently developed CNC programming tools with intelligence features for the purpose of efficiency evaluation [18] are still limited to level two. In other words, CAPP tools and domain applications for the level three to solve realistic problems may be rarely existent from the viewpoint of Industry 4.0 architecture. However, CNC CAPP shows a potential of upgrading the ability and potency of self-adaptability features in toolpath planning for a manufacturing enterprise.

The major challenge of CAPP involves conversion from skill/experience to knowledge or signal/data to information [19]–[21] when pursuing an intelligent factory. And Industry 4.0 featured components, such as semantic framework and cyber physical system (CPS), extend modelling and decision-making technologies that stem from conventional optimal searching algorithms by integrated synthesis. The key sources include

- Simulated Annealing (SA) scenarios, that are recognized as a combinational optimization algorithm, focused on differentiating the so-called neighborhood space from the current configuration to deal with perturbation effectively [24]; and
- Genetic Algorithm (GA) scenarios, that are rooted in the mechanism of evolution and natural genetics, which have evolved into the field of IC substrate drilling toolpath optimization [25].

The aforementioned optimization principles contribute to the proposed algorithms in this study. As opposed to so-called contouring operational control on CNC motion, the developed CAPP focuses on PTP based realistic and practical processes. The purpose of planning is to optimize the sequence and frequency of switching and path traversing in an intelligent clustering manner. The outcome is applicable to Industry-3.X machining tools and their continuous multi-axial motion control. The objective of this research is to fulfill the problem-solving reconfiguration level [16] on practical CNC CAPP cases. Relevant Industry 4.0 attributes, such as collaborative diagnostics and decision-making scenarios, are hinged on the adoption of digitized machining process parameters. Through bottom-up (from conversion to reconfiguration) intelligent integration of information and communication among enterprise stakeholders, the methodology can be an enabler for the Industry 4.0 driven CNC CAPP. The next section addresses the innovative means of getting geometrical controlling points from a workpiece and embedded into model computing for the process planning.

III. DESIGN OF INTELLIGENT CONTROLLING ALGORITHMS

In accordance with previously mentioned platforms, Wang *et al.* [22] viewed Industry 4.0 as an initiative to drive traditional manufacturing systems into full integration of physically embedded internet of things (IoT). Further highlighted are three compatible implementation features: value network, value chain and interconnected infrastructure. The critical novelty of the proposed CNC CAPP is divided into three aspects as follows:

1. Implementation of horizontal, point-to-point and vertical integration, respectively [22];
2. Aggregation of decision-making parameters: time resolution, manufacturability and efficiency [18], [23]; and
3. Reconfiguration of such variables' self-optimization derived from self-adaptability [16].

Correspondingly, there are three steps of optimization to represent featured Industry 4.0 components.

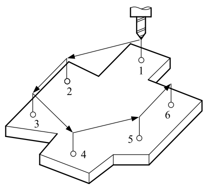

FIGURE 1. A planned tool path machining all holes with the same size.

A. OPTIMIZATION IN A SINGLE OP

TSP is suitable for planning all holes with the same size using the same process, as shown in Fig. 1. There are two prerequisites: (1) each hole being sequentially allocated with least non-value added motion cost and (2) fulfillment of a set of constraints [26]. The solution space should allow iterative improvement possibility like SA.

In TSP, the $V = \{1, \cdots, \mathrm{n}\}$ and c_{ij} represent the holes and the cost associated with the route from hole i to hole j. By taking into consideration both the so-called Hamiltonian cycle [26] and complete digraph [10], the cost function in a tabu searching scenario may adapt as:

$$Minmize \sum_{i \neq j} c_{ij} x_{ij} \tag{1}$$

$$\text{Subject to: } \sum_{i \neq j} x_{ij} = 1 i \in V \tag{2}$$

$$\sum_{i \neq j} x_{ij} = 1 j \in V \tag{3}$$

$$\sum_{i,j \in V} x_{ij} \leq n - 1 \tag{4}$$

$$x_{ij} \in \{0, 1\} \quad i, j \in V \tag{5}$$

Here $c_{ij} = c_{ji}$ is a symmetric scenario. Constrains (2) and (3) ensure that the in and out degree of each hole is one i.e., each hole is visited exactly once. Constrain (4) is sub-tour elimination and ensures that a complete Hamiltonian cycle is obtained rather than a series of disjointed cycles. As demonstrated, it took 34 and 63 seconds to converge our developed searching algorithm for 50 and 70 holes, respectively. Therefore, $\sqrt{n}$ where n stands for the dataset size is suitable for determining the length of the tabu list [27].

B. OPTIMIZATION IN MIXED OPS

This category of machining process involves holes with different sizes and operations, leading to OP variations in tool change and machining process sequence for each hole. It is desirable to reduce tool change frequency in addition to previously mentioned object functions as non-productive activities. For example, a workpiece is defined as a compound with two subsets, namely Π for the tool set and J for the process set. Assuming $\prod = \{T_1, T_2, \ldots, T_m\}$ where m types of tools (T_i) support n types of work (W_j) in queue of machining, we then define $J = \{W_1, W_2, \ldots, W_n\}$ where a specific tool corresponds with work, i.e. $W_j(T_i)$, for a predetermined hole size that is identified as internal diameter parameter.

TABLE 1. Mixed internal diameter (I.D.) sizes / machining work order (W.O.).

W.O. / I.D.	Center Hole Drilling	Drilling	Tapping	Chamfering
Ø12.0	Ø3.0 center drill	Ø12.0 drill		Ø18.0 liner chamfer drill
Ø14.5	Ø3.0 center drill	Ø8.5 drill Ø14.5 drill		Ø18.0 liner chamfer drill
Ø11.0	Ø3.0 center drill	Ø11.0 drill	Ø14.5 tapping drill	
Ø10.5	Ø18.0 liner chamfer drill	Ø10.5 drill		

1) TWO-WAY SCHEME

As shown in Table 1, the two-way scheme optimizes combinational size and sequence for each hole identified in a workpiece. In the row-wise perspective, each hole in rows will list a needed tool or tools that get sorted in an ascending order for a valid OP such as center hole drilling, drilling, tapping or chamfering. In the column-wise perspective, similarly, each OP in columns will list planned tool or tools to form a zig-zag OPs sequence.

TABLE 2. Mixed operations in tabu initial parametric search list.

W.O. / I.D.	Center Hole Drilling	Drilling	Tapping	Chamfering
Ø12.0	$\boldsymbol{W_1(T_1)}$	$\boldsymbol{W_2(T_2)}$		$\boldsymbol{W_3(T_3)}$
Ø14.5	$W_4(T_1)$	$W_5(T_4)$ $W_6(T_5)$		$W_7(T_3)$
Ø11.0	$W_8(T_1)$	$W_9(T_6)$	$W_{10}(T_7)$	
Ø10.5	$W_{11}(T_3)$	$W_{12}(T_8)$		

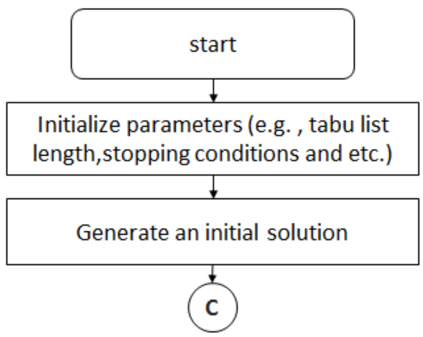

FIGURE 2. Initial stage.

2) TABU INITIATIVE

In order to obtain the relative coupling entity, in terms of $W_j(T_i)$, among the related cells in rows and in columns, a tabu table is arranged, as shown in Table 2. Tabu list is defined as T that forms initial code that holds both geometry and motion statements, as shown in Fig. 2, which is followed by a comprehensive search stage that is illustrated in Fig 3 and Table 2.

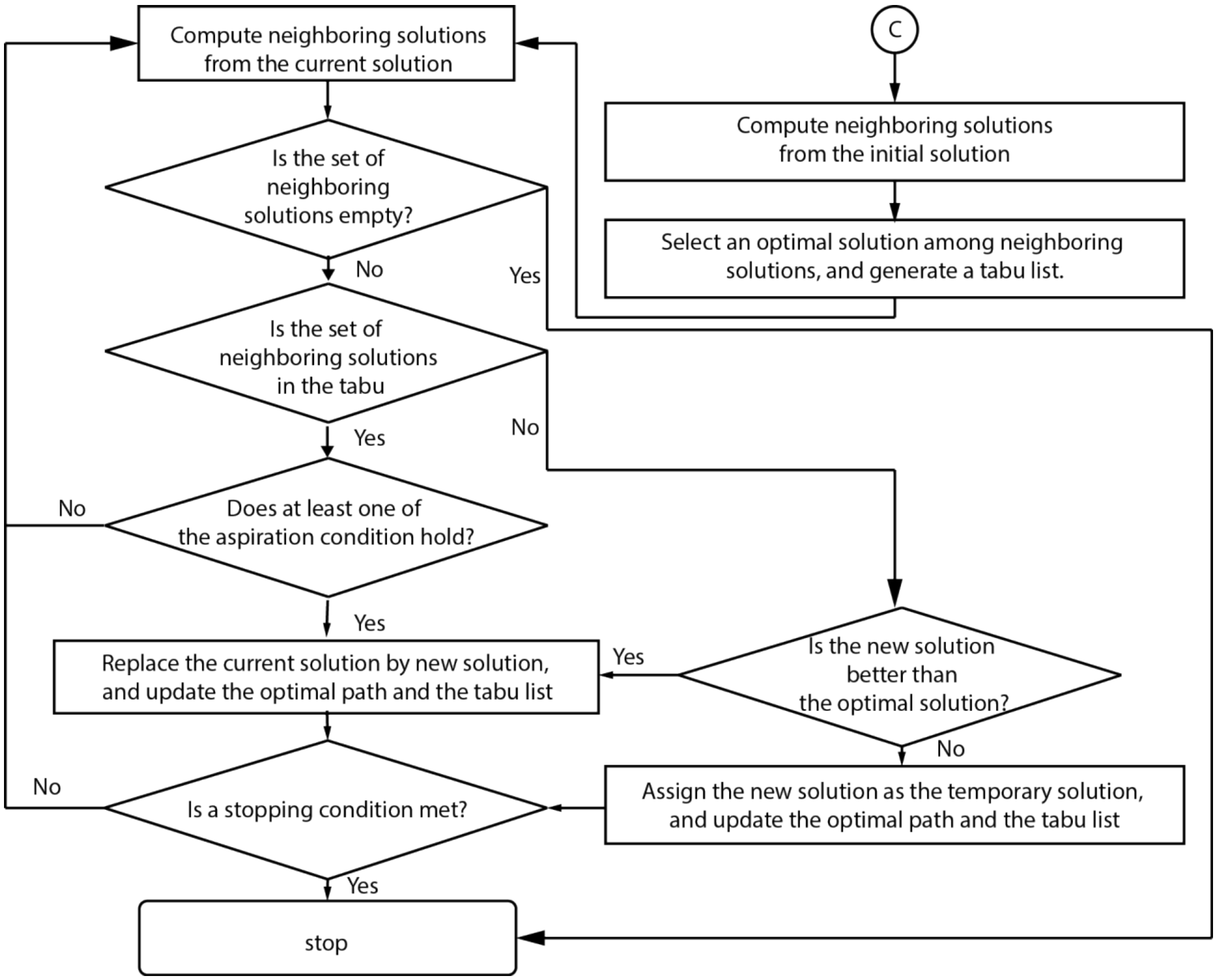

FIGURE 3. Searching stage.

Compared to the single OP optimization using conventional TSP approach, the initial scheduling renders process parameters to form the tabu list to prepare for the following tabu search conditionally. To demonstrate a higher level of value added decision making process in an interenterprise-wide CAM infrastructure, work order clusters are used, that is set for a hole feature with Ø12.0, shown in the second row of Table 2. It is the precedence relation that needs to be satisfied first before the next feasible step can be applied within the same cluster. That is, center hole drilling starts first, which is followed by drilling, and chamfering ends later. Therefore, there exists nested criteria to check the precedence relation for every iteration when executing a tool and/or local TSP optimization. An overview of a converged result through a tabu search on a work order (W.O.) scheduling, shown in Fig. 4, reveals end-to-end digitization of critical physical machining assets for a human machine co-working platform.

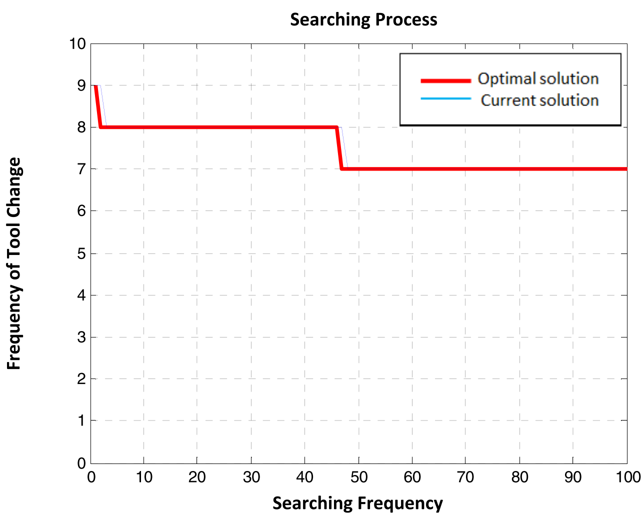

FIGURE 4. Converged result after tabu search on W.O. scheduling.

3) TABU ALGORITHM

The proposed two-stage-hybrid tabu algorithm starts with the initial stage, as shown in Fig. 2, that is followed by the searching stage, as shown in Fig. 3. Functionalities of all blocks in Fig. 3 are to optimize a series of consecutive iterations by switching between local neighborhood of trial solution and global feasible solution, considering $W_j(T_i)$.

TABLE 3. The initial hole processing with a total work order.

Finished Procedure (Total Work Order)

I.D. \ Tool	T_3	T_1	T_6	T_4	T_7	T_8	T_2	T_3	T_5	T_3
ϕ12.0		W_1					W_2	W_3		
ϕ14.5		W_4		W_5					W_6	W_7
ϕ11.0		W_8	W_9		W_{10}					
ϕ10.5	W_{11}					W_{12}				
	1	2	3	4	5	6	7	8	9	10

Processing Sequence (Frequency of Tool Change)

As mentioned before, the tabu algorithm generated an initial solution, as shown in Table 3, to process holes with various stages for the total work order. In other word, a feasible solution from the initial stage leads to a preliminary work order as:

Preliminary W.O. $W_{11}(T_3)_\rightarrow W_8(T_1)_\rightarrow W_1(T_1)_\rightarrow W_4(T_1)_\rightarrow W_9(T_6)_\rightarrow W_5(T_4)_\rightarrow W_{10}(T_7)_\rightarrow W_{12}(T_8)_\rightarrow W_2(T_2)_\rightarrow W_3(T_3)_\rightarrow W_6(T_5)_\rightarrow W_7(T_3)$

It is expected that participating personnel (machinists, maintenance specialists, process associates, financial decision makers and etc.) can access the bottom-up information directly or indirectly through internal enterprise-wide cloud storage files. It is worth mentioning that this stage is to validate and/or verify the feasible arrangement of a scheduled work order.

TABLE 4. The evolved hole processing with a total work order.

Finished Procedure (Total Work Order)

I.D. \ Tool	T_1	T_4	T_6	T_2	T_5	T_7	T_3	T_8
ϕ12.0	W_1			W_2			W_3	
ϕ14.5	W_4	W_5			W_6		W_7	
ϕ11.0	W_8		W_9			W_{10}		
ϕ10.5							W_{11}	W_{12}
	1	2	3	4	5	6	7	8

Processing Sequence (Frequency of Tool Change)

Further calculation results in the optimum solution, as shown in Table 4, when the tabu search reaches the convergence stage and generates an improved work order as:

Optimal W.O. $W_4(T_1)_\rightarrow W_1(T_1)_\rightarrow W_8(T_1)_\rightarrow W_5(T_4)_\rightarrow W_9(T_6)_\rightarrow W_2(T_2)_\rightarrow W_6(T_5)_\rightarrow W_{10}(T_7)_\rightarrow W_{11}(T_3)_\rightarrow W_7(T_3)_\rightarrow W_3(T_3)_\rightarrow W_{12}(T_8)$

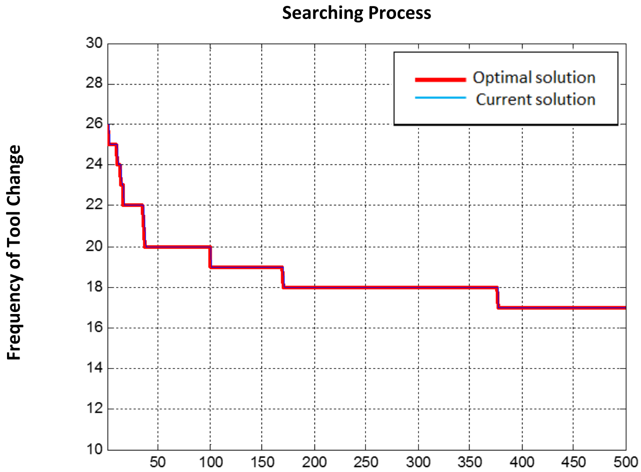

FIGURE 5. Converged tabu search on a W.O. with forty hole configurations.

In this example, tool change frequency resulted in more than 20% improvement in efficiency; work sequential complexity ratio led to more than 30% reduction in the manufacturability aspect. In other words, the tabu search obtained seven tool changes and two mixed OPs in Table 4 from an initial trial solution of nine times and three mixed OPs in Table 3. Once again, the convergence in Fig. 4 is the result of an optimum solution that is concluded in Table 4. As another illustration for the viewpoint of scalability, a similar case with fifteen tools underwent the mixed-OP tabu search, the converged result, shown in Fig. 5, also displayed a satisfactory outcome.

FIGURE 6. Precision mini 5-axis CNC machining center (Intek Co.).

IV. PERFORMANCE EVALUATION AND ANALYSIS

The five-axis CNC tapping machine, shown in Fig. 6, was equipped with the proposed and compared algorithms embedded in a developed firmware interface sub-system to interact with the machine controller. There were twelve tools that were involved to process XYZ + BC axial machining on five sequential surfaces after path and order generation by software.

A multi-faceted workpiece, as shown in Fig. 7, was used to demonstrate the effectiveness of the research model in the project. Partial simulated results are shown in Figs. 8-14.

By executing the sequential intelligent reasoning on the top, left-hand-side, right-hand-side, frontal and back view,

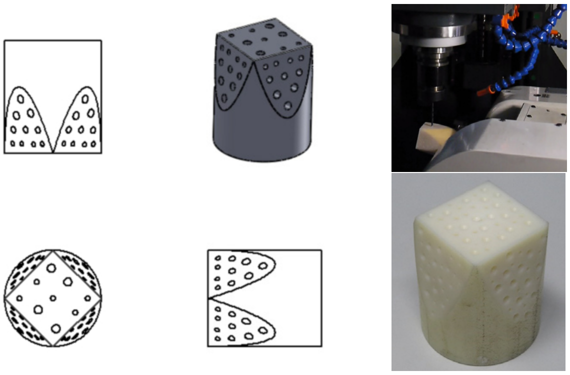

FIGURE 7. Demo workpiece from modeling to machining to finished stages.

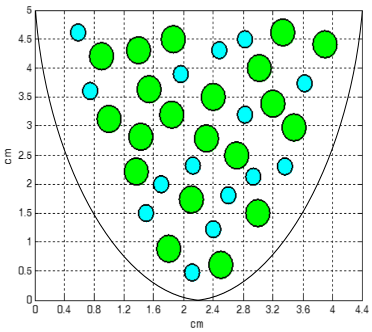

FIGURE 8. Holes cloud clustering identified initially.

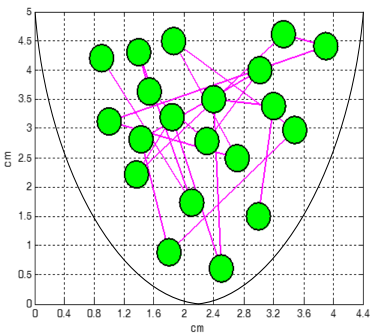

FIGURE 9. G1 path generation via random method.

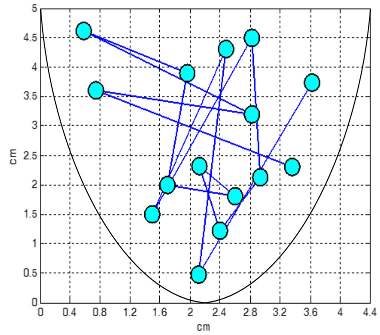

FIGURE 10. G2 path generation via random method.

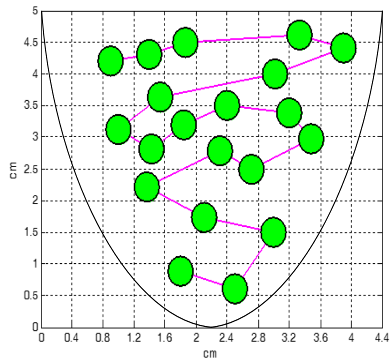

FIGURE 11. G1 path generation via zig-zag method.

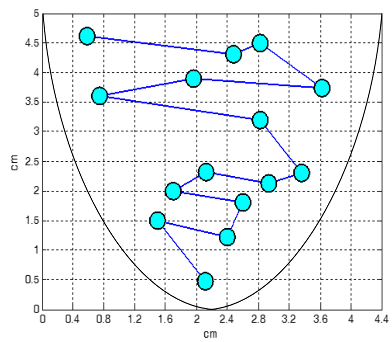

FIGURE 12. G2 path generation via zig-zag method.

respectively, the interface unit the map the digitized parameters into work order to perform combinatorial optimization, followed by the NC code generation.

Finally, the sub-system calls operational associates for validating the whole process and verifying the decision before downloading and machining actually take place. The comparisons between the initial solutions, that represent typical experimental groups, and the post TS optimization, is two-folds. The single OP tabu search holds an advantage of toolpath generation, as shown in Table 5. The cost function converts the toolpath distance into value-added path, and the machining time into value-added time. And the mixed OP tabu planning exceeds in toolpath and time sequencing complexity the standard operating procedure (SOP), as shown in Table 6. The proposed i-CAPP demonstrates decision-making advantages over a SOP that is typically documented in an operational menu. It further illustrates how the built-in intelligence features collaborate with domain expert's procedure when complexity of machining criteria increases.

V. DISCUSSION

Trials on large data sets show the stable results. When the data sets are small, it is possible that the effectiveness of finding the optima may be limited. As a caveat, therefore, a study that includes small number of holes with less size variations may show a discrepant result.

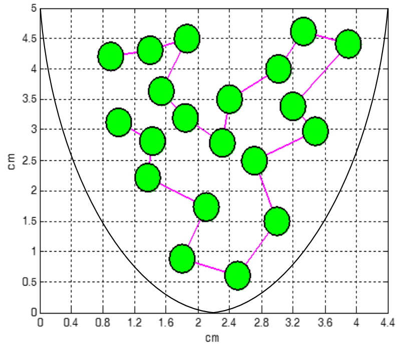

FIGURE 13. G1 path generation via tabu method.

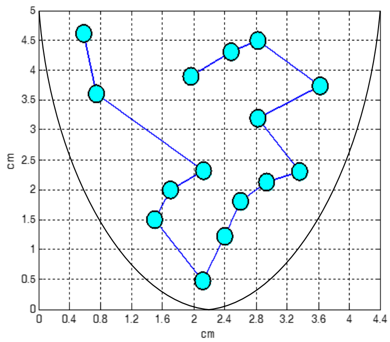

FIGURE 14. G2 path generation via tabu method.

TABLE 5. Stage-one evaluation on single OP planning.

Planning Algorithm / Performance Index	tubu over	
	random	zig-zag
value-added path	59.07 % increase	30.21% increase
value-added time	32.06% increase	8.94% increase

TABLE 6. Stage-two evaluation on mixed OP planning.

Planning Algorithm / Performance Index	tubu over
	standard operating procedure
tool change frequency	28% increase
value-added time	5% increase

VI. CONCLUSIONS

Industry 4.0 stimulates profit making in a reconfigurable ecosystem where manufacturing enterprises strive to create and sustain value network by removing wastes of all kinds. Industry 4.0 evolves conventional manufacturing processes into intelligent and interconnected agents that can complement each other autonomously to reduce processing costs. In pursuing the Industry 4.0 readiness, both implementation outlook and platform are critical. Based on Industry 4.0 initiatives, a survey from industry leaders reveals a potential area of using data analytics to enhance the partnership among manufacturing value-chain stakeholders [15]. Meeting customer requirements, such as bottom-line costs and throughput demands, and improving operational performance draw as high as 72% consensus [15]. Consequently, the process-planning paradigm calls for transforming passive knowledge database into an intelligent CAPP "info-base". In our case, the developed algorithms with transferability respond decision-making scenarios in manufacturing virtual reality that is augmented and optimized through an integrated network.

This paper has demonstrated how to construct an i-CAPP on a five-axis CNC tapping machine. By applying hybrid-two-stage optimization algorithms, namely TPS and novel TS methods, our automatically generated code for CNC with the embedded CAPP successfully machines a workpiece. Moreover, verification of the manufacturability and efficiency to highlight Industry 4.0 performance indicators results in an alignment with opinions from industry experts in terms of operational performance [15]. End-to-end digitization of critical physical machining assets are enabled through a series of PTP OPs to realize an intelligent integration of CNC practices. This paper has also established a roadmap of next generation CAPP with advances in synergy of variant and generative approaches. The CNC processing performance indices become transparently tangible and sharable among manufacturing value-chain stakeholders. By streamlining communication and information of process planning, this research achieves the problem-solving reconfiguration level [16]. As a result, it demonstrates the Industry 4.0 readiness by developing a realistic and practical CNC CAPP intelligence kernel.

To leap into the on-going Industry 4.0 innovation, the proposed CNC CAPP model may be expanded with other intelligent features by using difference evaluation scenarios in CNC programming. A uniform application programming interface (API) on self-adaptive variant/generative optimization may prevent small data sets from compromising the effectiveness of finding the optima. In the meantime, the research study can be extended into different operational processes such as contour machining. Furthermore, based on the sound vertical integration on the machining aspect, revitalizing horizontal integration is a continuous journey. It stretches beyond the internal operations by reconfiguring interconnected value chain parameters and variables that are recognized by manufacturing value-network stakeholders.

REFERENCES

[1] C. R. Boër, M. Petitti, F. Lombardi, and J.-P. Simon, "A CAPP/CAM expert system for a high productivity, high flexibility CNC turning center," *CIRP Ann.-Manuf. Technol.*, vol. 39, no. 1, pp. 481–483, 1990.

[2] B. Denkena, M. Shpitalni, P. Kowalski, G. Molcho, and Y. Zipori, "Knowledge management in process planning," *CIRP Ann.-Manuf. Technol.*, vol. 56, no. 1, pp. 175–180, 2007.

[3] X. Zhang, A. Nassehi, M. Safaieh, and S. T. Newman, "Process comprehension for shopfloor manufacturing knowledge reuse," *Int. J. Prod. Res.*, vol. 52, nos. 23–24, pp. 7405–7419, 2013.

[4] O. Jaider, A. Rechia, A. El Mesbahi, and H. Zarkti, "An automatic feature-based cutting tool selection approach for turning process," *Int. J. Current Eng. Technol.*, vol. 5, no. 5, pp. 1–18, Oct. 2015.

[5] W. A. Khan, D. R. Hayhurst, and C. Cannings, "Determination of optimal path under approach and exit constraints," *Eur. J. Oper. Res.*, vol. 117, no. 2, pp. 310–325, 1999.

[6] W. Xiang, C. W. Chuen, C. M. Wong, and L. H. Yam, "A generative feature-based CAPP/CNC system for hydraulic manifold blocks," *Int. J. Adv. Manuf. Technol.*, vol. 19, no. 11, pp. 805–811, 2002.
[7] S. Lu, T. Yu, and T. Liu, "Research on CAPP technology oriented to CNC," in *Proc. 9th Int. Conf. Control, Autom., Robot. Vis.*, Dec. 2006, pp. 1–5.
[8] S. Lu, X.-L. Cao, Z.-J. Cai, G.-R. Zeng, and T. Liu, "Application and execution of CNCbCAD&CAPP technology in INC," in *Proc. Medit. Conf. Control Autom.*, Jun. 2007, pp. 1–5.
[9] U. Manber and S. Israni, "Pierce point minimization and optimal torch path determination in flame cutting," *J. Manuf. Syst.*, vol. 3, no. 1, pp. 81–89, 1984.
[10] K. Castelino, R. D'Souza, and P. K. Wright, "Toolpath optimization for minimizing airtime during machining," *J. Manuf. Syst.*, vol. 22, no. 3, pp. 173–180, 2003.
[11] C. Y. Tsai, C. H. Liu, and Y. C. Wang, "Application of genetic algorithm on IC substrate drilling path optimization," in *Proc. Int. Conf. Adv. Mech. Syst.*, Sep. 2012, pp. 18–21.
[12] L. Chih-Ching, "A new approach to CNC tool path generation," *Comput.-Aided Design*, vol. 30, no. 8, pp. 649–655, 1998.
[13] J. H. Cho, J. W. Kim, and K. Kim, "CNC tool path planning for multi-patch sculptured surfaces," *Int. J. Prod. Res.*, vol. 38, no. 7, pp. 1677–1687, 2000.
[14] V. M. Pedagopu and M. Kumar, "Integration of CAD/CAPP/CAM/CNC to augment the efficiency of CIM," *Int. Rev. Appl. Eng. Res.*, vol. 4, no. 2, pp. 171–176, 2014.
[15] B. Misthal, R. Geissbauer, and J. Vedso. (Aug. 1, 2016). "Industry 4.0: Building the digital enterprise: Industry key findings," PWC. [Online]. Available: http://www.pwc.com/gx/en/industries/industrial-manufacturing/publications/building-digital-enterprise.html
[16] M. K. Adeyeri, K. Mpofu, and T. A. Olukorede, "Integration of agent technology into manufacturing enterprise: A review and platform for industry 4.0," in *Proc. 5th Int. Conf. Ind. Eng. Oper. Manage. (IEOM)*, 2015, pp. 1–10.
[17] D. Wu, J. Terpenny, and D. Schaefer, "Digital design and manufacturing on the cloud: A review of software and services," *Artif. Intell. Eng. Design Anal. Manuf.*, vol. 31, no. 1, pp. 104–118, 2017.
[18] S. Klancnik, M. Brezocnik, and J. Balic, "Intelligent CAD/CAM system for programming of CNC machine tools," *Int. J. Simul. Model.*, vol. 15, no. 1, pp. 109–120, 2016.
[19] J. Zhang and K. Agyapong-Kodua, "Integrated ontologies in support of factory systems design," *IFAC-PapersOnLine*, vol. 48, no. 3, pp. 2095–2102, 2015.
[20] L. Wang and G. Wang, "Big data in cyber-physical systems, digital manufacturing and industry 4.0," *Int. J. Eng. Manuf.*, vol. 6, no. 4, pp. 1–8, 2016.
[21] F. Klocke, G. Spöcker, T. Huwer, T. Bobek, and K. Arntz, "Reducing data loss within adaptive process chains in the context of commonly-used CAx systems," *Prod. Eng.*, vol. 9, no. 3, pp. 307–316, 2015.
[22] L. Wang, M. Törngren, and M. Onori, "Current status and advancement of cyber-physical systems in manufacturing," *J. Manuf. Syst.*, vol. 37, pp. 517–527, Oct. 2015.
[23] C. Weidig, C. Steimer, and J. C. Aurich, "Process planning and decentralised process control for cybertronic production systems," *Appl. Mech. Mater.*, vol. 794, pp. 486–493, Oct. 2015.
[24] K. Lee, *Principles of CAD/CAM/CAE Systems*. Massachusetts, MA, USA: Addison Wesley Longman, 1999.
[25] D. L. Yu and H. Shihtao, "Application of immune algorithm on IC substrate drilling path optimization," *J. Qual.*, vol. 19, no. 4, pp. 339–348, 2012.
[26] M. M. Flood, "The traveling-salesman problem," *Oper. Res.*, vol. 4, no. 1, pp. 61–75, 1956.
[27] F. Glover and M. Laguna, "Tabu search," in *Modern Heuristic Techniques for Combinatorial Problems*, C. R. Reeves, Ed. Oxford, U.K.: Blackwell, 1993, pp. 70–150.

CHIN-SHENG CHEN received the Ph.D. degree in mechanical engineering from National Chiao Tung University, Hsinchu, Taiwan, in 1999. He was a Researcher with Sintec Technology Company Ltd., from 1999 to 2000 and a Research and Development Manager of TECO Electric & Machinery Company Ltd., from 2000 to 2002. In 2002, he joined the Graduate Institute of Automation Technology, National Taipei University of Technology, Taipei, Taiwan, as an Assistant Professor, where he is currently a Professor and Director. He has published his research in more than 150 journal and conference papers and book chapters. His research interests include intelligent motion control, mechatronics, and machine vision. He received the Outstanding Research Award from the College of Mechanical and Electrical Engineering, Taipei TECH, in 2013 and 2014.

YIN TUNG ALBERT SUN received the Ph.D. degree in industrial engineering with a concentration on automated manufacturing systems from the University of Cincinnati, Cincinnati, OH, USA, in 1999. He joined the Department of Engineering, St. Mary's University, San Antonio, TX, USA, as an Assistant Professor, in 1999. Prior to his academic career, he was an Applications Engineer with Brown & Sharpe Manufacturing Company Ltd., Cincinnati. He served as a Research Advisor of Hawthorne & York International, Ltd. (in bioengineering) from 1999 to 2005. Since 2005, he has been a Research Advisor with the University of Texas at San Antonio Health and Science Center. He is currently with the National Taipei University of Technology. His research interests include lean manufacturing, manufacturing systems integration, CAD/CAM/CAPP/CAI, and industry 4.0 engineering education.