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Framework of automated value stream mapping for lean production under the Industry 4.0 paradigm*

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Abstract: For efficient use of value stream mapping (VSM) for multi-varieties and small batch production in a data-rich environment enabled by Industry 4.0 technologies, a systematic framework of VSM to rejuvenate traditional lean tools is proposed. It addresses the issue that traditional VSM requires intensive on-site investigation and replies on experience, which hinders decision-making efficiency in dynamic and complex environments. The proposed framework follows the data-information-knowledge hierarchy model, and demonstrates how data can be collected in a production workshop, processed into information, and then interpreted into knowledge. In this paper, the necessity and limitations of VSM in automated root cause analysis are first discussed, with a literature review on lean production tools, especially VSM and VSM-based decision making in Industry 4.0. An implementation case of a furniture manufacturer in China is presented, where decision tree algorithm was used for automated root cause analysis. The results indicate that automated VSM can make good use of production data to cater for multi-varieties and small batch production with timely on-site waste identification and analysis. The proposed framework is also suggested as a guideline to renew other lean tools for reliable and efficient decision-making.

Key words: Value stream mapping (VSM); Root cause analysis; Automated decision-making; Lean production tools; Industry 4.0
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1 Introduction

To meet diverse customer needs and rapidly respond to market dynamics, the production mode of manufacturing enterprises has shifted from mass production to multi-varieties and small batches. Multi-variety and small batch oriented manufacturing is more complex, featuring frequent production line changes and difficult standard time setting, which brings new challenges to manufacturers in cost reduction, and quality and productivity improvements (Dombrowski et al., 2017; Ku et al., 2020). To cope with these challenges, manufacturers are eager to find better ways to incorporate lean production tools in the context of Industry 4.0 (Mayr et al., 2018; Rossini et al., 2019). The traditional lean production tools were developed in the 1990s and initially used in simple and stable environments (Ramadan et al., 2020). The development of lean production tools from Industry 1.0 to 4.0 is shown in Fig. 1.

In Industry 3.0, lean production tools were developed in parallel with internet and programmable logic controller (PLC) to jointly solve the problems. Over time, the lean house concept was gradually formed. In Industry 4.0, many researchers began to think about the development of a lean house. Lean production tools also need to integrate new

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technologies to meet the challenge caused by multi-varieties and small batches. However, application of traditional lean production tools relies mostly on manual data collection and analysis, which is time-consuming and costly to apply (Uriarte et al., 2018) and requires workers to be highly experienced in increasingly complex and dynamic environments (Longo et al., 2017). This often hinders the awareness, delays the decision response, and misses the improvement opportunity. With advances in information and communication technology (ICT), such as the internet of things (IoT), smart sensors, and big data, manufacturers have many technologies available to achieve digitalization and intelligence. This evokes new ideas for the applications of lean production tools (Ramadan et al., 2020).

Lean production tools include 5S, Kanban, value stream mapping (VSM), and total quality management (TQM), which are used to reduce cost, control process quality, and improve productivity by eliminating waste. Among these tools, VSM is a fundamental tool which can reduce the waste in material and information flows (Tamás, 2016), identify bottlenecks, and indicate production performance, such as processing time and work-in-process (WIP) inventory (Solding and Gullander, 2009; Rahani and Al-Ashraf, 2012; Rohani and Zahraee, 2015). Although VSM can identify waste and bottlenecks, the root causes require intensive on-site investigations and manual analysis which hinders decision-making efficiency, particularly in a dynamic and complex manufacturing environment. Data-information-knowledge mapping towards decision-making in the context of Industry 4.0 is also important (Badia, 2014; Papacharalampopoulos et al., 2020). Therefore, to make good use of the streamed data and improve decision-making efficiency, we propose a systematic framework of automated VSM for lean production under the Industry 4.0 paradigm. The framework consists of three levels and introduces a new approach to collecting data, visualizing on-site manufacturing performance, and mining root causes automatically. These provide operators with the real-time production status of a smart workshop and a scientific decision basis

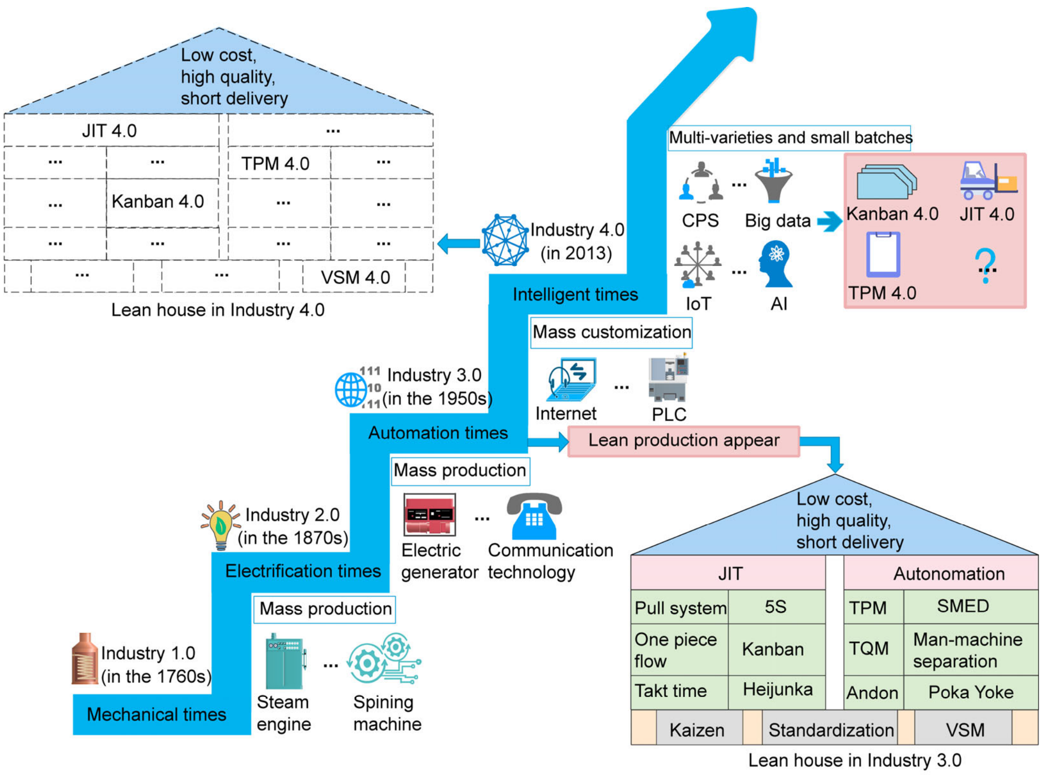

Fig. 1 Development of lean production tools in Industry 1.0–4.0

JIT: just-in-time; TPM: total productive maintenance; CPS: cyber-physical systems; AI: artificial intelligence; SMED: single minute exchange of die which is suitable for multi-varieties and small batches, and features high flexibility and dynamic variability.

2 Literature review

To further improve the competitiveness of manufacturing factories, the German government proposed the Industry 4.0 strategy in 2013 (Kagermann et al., 2013; Drath and Horch, 2014). It is defined as "a real-time, intelligent, and digital network of people, devices, and objects for managing business processes and value creating networks," which is enabled by advanced, cost-effective ICTs. These ICTs facilitate end-to-end communication among smart machines, products, systems, and operators in production and logistics processes, towards comprehensive data analysis, fine process control, and continuous improvements. They promote the maturing applications of pillar technologies, such as cyber-physical systems (CPS), IoT, cloud platforms, and radio frequency identification (RFID) (Fonseca, 2018). CPS can integrate with physical entities related to production systems (Lins and Oliveira, 2020). It ensures data collection and processing and meets multiple purposes of an organization (Xu et al., 2018). IoT is another main enabler for digitalization and smart factories which has changed the operation and role of industrial systems (Peruzzini et al., 2017). Manufacturing enterprises should be efficient, productive, and competitive to survive in complex and dynamic markets, and an Industry 4.0 strategy to achieve digitization and intelligence can help achieve this. The potential short and long term impacts of Industry 4.0 on industries in the global market are huge, and can meet the needs of customers in mass production (Xu et al., 2018).

2.1 Lean production tools in Industry 4.0

Lean production, or lean management, is recognized as the groundwork for Industry 4.0 (Prinz et al., 2018). Many researchers wanting to achieve a higher lean level have focused on how to use and improve existing lean production tools (Buer et al., 2018). ICTs can be incorporated in lean production tools in highly-customized, dynamic, and complex manufacturing environments (Kolberg et al., 2017; Buer et al., 2018; Prinz et al., 2018). Researchers also stated that the integration of these technologies with lean production tools can help manufacturing enterprises further improve production efficiency, reduce cost, and improve quality (Khanchanapong et al., 2014; Sanders et al., 2016; Moeuf et al., 2018). Mayr et al. (2018) suggested the introduction of various lean tools in Industry 4.0 such as Kanban 4.0, Just-in-time (JIT) 4.0, total productive maintenance (TPM) 4.0. They adopted a cloud-based, data-driven approach to improving the efficiency of implementing TPM. Wagner et al. (2017) introduced a conceptual integration framework enabled by CPS and JIT, and described the operational procedure. Shahin et al. (2020) proposed the fundamental elements and an implementation framework for cloud Kanban. Kolberg et al. (2017) described the combination of ICTs and Kanban in lean automation practice.

Although some lean production tools have been studied and improved in Industry 4.0, there is still a lack of a systematic and practice-oriented framework with holistic approaches to integrate lean tools (Ma et al., 2017; Prinz et al., 2018). Deuse et al. (2015) pointed out that existing integration frameworks cannot sufficiently reflect technology, human, and other elements.

2.2 Value stream mapping in Industry 4.0

VSM is often regarded as the starting point of lean improvement, and is of great significance to the promotion of lean projects (Tamás, 2016). However, traditional VSM is used mainly in serial production lines that produce a single product or a single family of products. It now faces challenges in data-rich environments performing real-time data processing, visualization, and decision-making assistance, and consequently is not well suited to manufacturing sites with diverse products, unstable batches, and frequent line changes (Dotoli et al., 2011; Schönemann et al., 2016; Balaji et al., 2020). Lian and van Landeghem (2007) pointed out that the data for VSM could be collected from multiple information systems, e.g. manufacturing execution system (MES), enterprise resource planning (ERP), and supply chain management (SCM), but poor data interoperability makes subsequent processing very time-consuming. Traditional VSM demonstrates the system performance during a certain time, which is a rather static and snapshot-type description of a production system, and it is costly to continuously visualize dynamic performance using VSM (Stadnicka and Litwin, 2019).

To solve the above challenges, some researchers have adopted Industry 4.0 technologies to improve the traditional VSM. In these studies, terms such as dynamic value stream mapping (DVSM) and value stream mapping 4.0 (VSM4.0) emerged. DVSM and VSM4.0 can display the real-time manufacturing performance of a whole process through the data acquisition system. DVSM mainly focuses on the waste of materials in the production process, while VSM4.0 focuses on the waste of the information flow. DVSM was defined as "a digitalized event-driven lean-based IT system that runs in real-time according to lean principles that cover all manufacturing aspects through a diversity of powerful practices and tools that are mutually supportive and synergize well together to effectively reduce wastes and maximize value" (Ramadan, 2016). Thus, DVSM connects production factors such as equipment, workers, and materials based on the integration of traditional VSM and Industry 4.0 technologies, so as to achieve real-time data transmission and display of production performance. With the development of Industry 4.0 technologies, some researchers applied RFID in value stream analysis to achieve the function of DVSM. Ramadan et al. (2017) integrated RFID technology with VSM and proposed a DVSM implementation framework which can automatically collect data of materials, personnel, machines, and other production factors to achieve real-time monitoring of manufacturing performance. Similarly, Chen and Chen (2014) presented an on-line RFID-based facility performance monitoring (ORFPM) system. This system uses wireless monitoring via RFID to automatically generate a real-time VSM using computer programming. Ramadan et al. (2017) expanded the function of DVSM by proposing an innovative real-time manufacturing cost tracking system (RT-MCT) which integrates VSM and RFID. The system addresses how to track and visualize the cost of development of individual products. CPS can also be integrated with traditional VSM. Huang et al. (2019) proposed a multi-layer DVSM, which integrates traditional VSM with a multi-agent system based on CPS technology. It can automatically collect data near a station through agents and display the changes of key indicators related to material and information flow in the production process of multi-parts in real time, or near real time. In addition to RFID and CPS technologies, researchers have combined the industrial internet of things (IIoT) with VSM. Balaji et al. (2020) introduced an integrated model of IIoT and VSM. By establishing a sensor system to collect workshop data and monitor site status in real time, a digital site can be observed comprehensively and observation accuracy can be improved, which helps managers to carry out improvement activities quickly based on experience. Some researchers (Solding and Gullander, 2009; Dotoli et al., 2011) also used discrete event simulation such as plant simulation and arena to build workshop models and automatically generate multi-part VSM using technologies such as AutoMod and MicroSoft Excel. The concept of VSM4.0 has also been proposed. Meudt et al. (2017) first introduced "VSM4.0" and extended the notation of process boxes. They focused mainly on detecting waste and loss in information flows. Hartmann et al. (2018) later gave the steps to design VSM4.0, which brought a new understanding of information in value streams. Table 1 summarizes the studies on the integration of VSM and industry 4.0 technologies.

However, such integration has focused mainly on real-time data collection and visualization, and few studies have reported on how to conduct in-depth data mining and automate root cause analysis. Papacharalampopoulos et al. (2020) emphasized that automatic root cause identification in a manufacturing site can greatly improve decision-making efficiency, which in practice still relies heavily on managers' experience and expertise. It is difficult and costly to cope with dynamic manufacturing conditions, and responses are often delayed. Chen and Chen (2014) used the 5Why tool to make improvement plans based on root cause mining, after automatically collecting data and creating VSM in an ORFPM system. The timeliness of the improvement effect needs further investigation.

Table 1 Summary of VSM and Industry 4.0 technology integration

Methodology	Data collection	Data visualization	Data analysis	Automated decision-making	Reference
RFID+VSM	✓	✓	–	–	Ramadan et al. (2012)
RFID+VSM	✓	✓	✓	–	Chen and Chen (2014); Ramadan et al. (2016)
CPS+VSM	✓	✓	✓	–	Huang et al. (2019)
IIoT+VSM	✓	✓	–	–	Balaji et al. (2020)
Simulation+VSM	✓	✓	✓	–	Dotoli et al. (2011); Solding and Gullander (2009)
IT system+VSM	✓	✓	✓	–	Meudt et al. (2017); Hartmann et al. (2018)

Badia (2014) proposed the data-information-knowledge hierarchy model, which explains the relationship between data, information, and knowledge in detail. This inspired our current study on VSM and Industry 4.0 technologies.

In this paper, a systematic framework of automated VSM for lean production under the Industry 4.0 paradigm is proposed to showcase how VSM can be rejuvenated in future manufacturing.

3 Framework of automated VSM

Our proposed framework follows the data-information-knowledge hierarchy model, and indicates how data can be collected in a smart workshop, processed into information, and then interpreted into knowledge (Fig. 2). It explains the automated data flow from smart workshop to knowledge level for analyzing root causes based on VSM.

Smart workshop applies intelligent technologies to realize autonomous perception, analysis, and adaptation in manufacturing sites (Gao et al., 2016). One important feature of smart workshop is the comprehensive collection of production data related to machines, personnel, and materials. Machine data can be acquired via PLC or sensors, which help managers better understand the manufacturing on-site situation. Workers can be equipped with RFID or barcode tags to record work flow information with corresponding readers. This is also feasible for WIP inventory and material data acquisition. In addition, the status of machines, personnel, and materials is critical for automated reasoning in root cause analysis.

3.1 Data level

The data level is responsible for data storage and pre-processing, which supports VSM visualization and further analysis. Production data in a smart workshop is streamed to the database via a cable/ wireless communication network, and integrated with other information systems, such as ERP, product data management (PDM), and SCM to provide supplier, process, and customer data according to the needs of VSM. Due to the residual issue of limited data interoperability among different information systems, there is a large amount of heterogeneous data in the database, which requires data cleaning, format conversion, and review for VSM.

3.2 Information level

The information level visualizes the preprocessed data based on VSM, displays the actual production situation, and reveals the instant cause of problems through basic statistics. Unlike the traditional VSM, the proposed VSM can be generated gradually along with the actual production progress. For example, when a part is being processed on the first machine, the associated VSM displays only its waiting time in the storage area, the WIP quantity before the machine, and the related machine data at that very moment. The subsequent processing status is not yet displayed. Personnel and material data can also be displayed. Statistical analysis will then be conducted to indicate production performance with visuals, such as actual progress, machine utilization, and output. To this point, data are considered to be converted into information, because they already carry practical meaning. When an incident happens, this information will be used for tracing and root cause analysis.

3.3 Knowledge level

The knowledge level is designed to support automated root cause analysis. The knowledge base includes an algorithm base, rule base, and lean

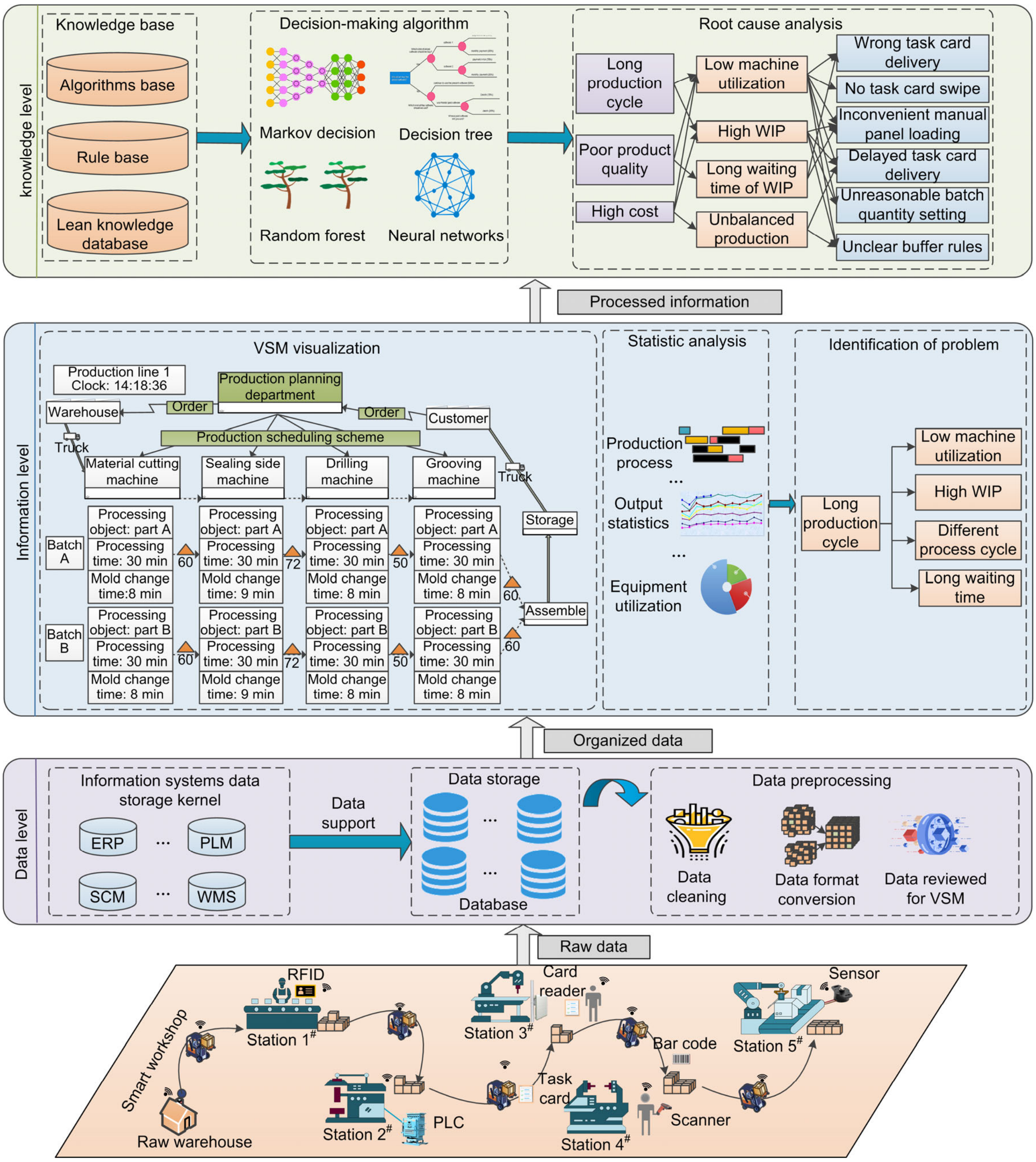

Fig. 2 Proposed systematic framework of automated value stream mapping

PLM: product lifecycle management; WMS: warehouse management system

knowledge base. An appropriate algorithm will be selected based on actual production know-how, and combined with predetermined rules to analyze the root cause of actual situation. To this point, information is considered to be processed into knowledge, because a manager can choose the most appropriate lean tool for improvement activity. Automated root cause analysis can significantly improve decision-making efficiency by reducing on-site investigation, which is labor-intensive and experience-dependent.

4 Implementation case

The proposed framework was implemented in a panel-type furniture workshop of a manufacturer in

Hangzhou, China. The workshop produces various types of office furniture, such as office desks and tables. A schematic diagram of the workshop is shown in Fig. 3.

The current production has been analyzed from three aspects: machines, personnel, and materials. Cutting machines, sealing side machines, drilling machines, and others are configured in four production lines based on furniture products. The materials are sent to the line inventory area using forklifts according to a predetermined delivery plan and transferred in batch within the workshop. Workers manually load the panel on a machine, process it when its task card and materials are ready, and unload after finishing. Previously, most production-related data in the workshop were recorded in paperwork and analyzed by workers, resulting in low utilization efficiency. The workshop has now implemented a preliminary data acquisition system, including RFID, barcode, readers/scanners, and external sensors. A manufacturing execution system was available to extract key information from the PLCs of machines. However, the data have not yet been fully used to assist decision-making.

4.1 Data level

To support root cause analysis and efficient decision-making, a data acquisition scheme was designed for this furniture workshop (Table 2). It shows the specific data types and collection methods according to VSM requirements.

The data on a task card, such as card number, delivery time, arrive time, and swipe time are also collected. Bill of material, process, customer, and supplier data are extracted from product lifecycle management (PLM), ERP, and SCM. These data are preprocessed and reviewed for VSM. The partial preprocessing process is shown in Fig. 4.

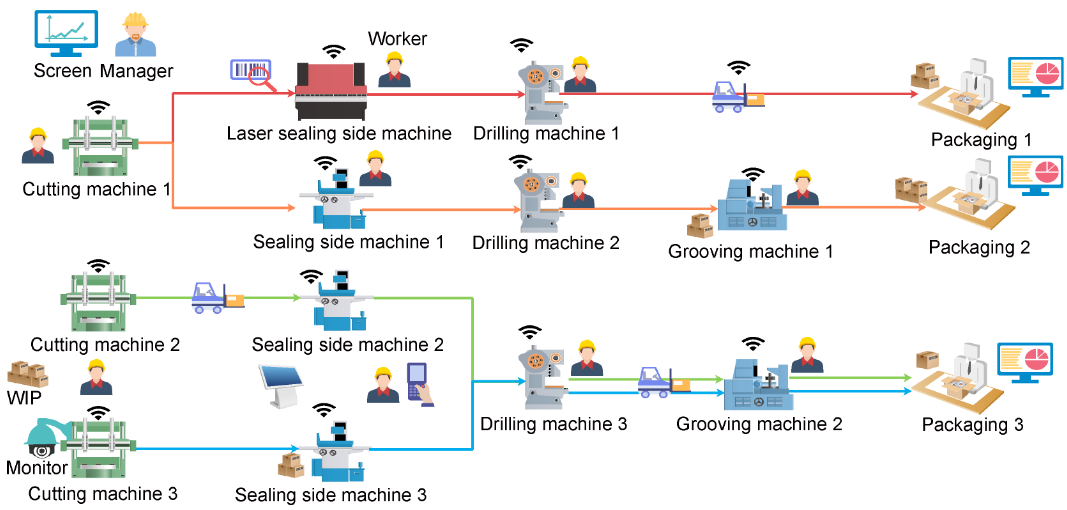

Fig. 3 A schematic diagram of the panel-type furniture workshop case study

Table 2 Designed data acquisition scheme

Data type	Specific data		Collection method
Machine data	Machine status	Machine number	PLC sensor
	Machine name	Start time	
	Completion time	Processing quantity	
	Changeover time	Frequency of failure	
	Mean failure time	Mean failover time	
Personnel data	Worker status	Worker number	RFID bar code
	Departure time	Entry time	
Material data	Order number	Material name	RFID bar code
	Material status	Material quantity	
	Material arrive time	Material waiting time	

machine number	start time	completion time	processing tine	Processing quantity	worker number
JG01	2019/9/1 10:53:00	2019/9/2 1:49:37	53797	40	111064
JG04	2019/9/1 15:				112900
JG02	2019/9/2 20:22:55	2019/9/2 11:21:03	10688	255	113250
FB07	2019/9/2 9:03:14				101165
DK04	2019/9/2 9:24:17	2019/9/2 21:49:24	1507	18	106204
FB06	2019/9/2 21:1				111636
DK01	2019/9/2 9:47:59	2019/9/2 9:59:00	661	8	117161
DK01	2019/9/2 9:59:30	2019/9/2 13:27:10	12460	12	117161
DK04	2019/9/2 10:25:48	2019/9/2 22:32:29	401	18	106204
DK04	2019/9/2 22:32:38	2019/9/2 10:35:58	200	18	106204
FB02		2019/9/2 23:06:52			112021
JG03	2019/9/2 13:51:56	2019/9/2 14:17:11	1515	30	112900
KC04	2019/9/2 13:59:46	2019/9/2 14:07:54	488	18	107175
KC04	2019/9/2 14:08:51111	2019/9/2 14:17:50	539	18	107175
FB02	2019/9/2 14:13:56	2019/9/2 14:22:54	538	30	112021
KC04	2019/9/2 14:20:59	2019/9/2 14:29:06	487	18	107175
KC04	2019/9/2 14			18	107175
JG02	2019/9/2 15:19:12	2019/9/2 15:29:15	603	6	113250
DK01	2019/9/2 15:24:59	2019/9/2 15:27:09	130	1	117161
JG02	2019/9/2 15:29:31	2019/9/2 15:41:18	707	21	113250
FB03	2019/9/2 15:37:10	2019/9/2 16:08:49	1899	30	100173
JG02	2019/9/2 15:41:46	2019/9/2 16:00:16	1110	38	113250
FB08	2019/9/2 15:4				115879

(a)

machine number	start time	completion time	processing tine	Processing quantity	worker number
JG01	2019/9/1 10:53:00	2019/9/2 1:49:37	53797	40	111064
JG02	2019/9/2 8:22:55	2019/9/2 11:21:03	10688	255	113250
DK04	2019/9/2 9:24:17	2019/9/2 9:49:24	1507	18	106204
DK01	2019/9/2 9:47:59	2019/9/2 9:59:00	661	8	117161
DK04	2019/9/2 10:25:48	2019/9/2 10:32:29	401	18	106204
DK04	2019/9/2 10:32:38	2019/9/2 10:35:58	200	18	106204
JG03	2019/9/2 13:51:56	2019/9/2 14:17:11	1515	30	112900
KC04	2019/9/2 13:59:46	2019/9/2 14:07:54	488	18	107175
KC04	2019/9/2 14:08:51	2019/9/2 14:17:50	539	18	107175
FB02	2019/9/2 14:13:56	2019/9/2 14:22:54	538	30	112021
KC04	2019/9/2 14:20:59	2019/9/2 14:29:06	487	18	107175
JG02	2019/9/2 15:19:12	2019/9/2 15:29:15	603	6	113250
DK01	2019/9/2 15:24:59	2019/9/2 15:27:09	130	1	117161
JG02	2019/9/2 15:29:31	2019/9/2 15:41:18	707	21	113250
FB03	2019/9/2 15:37:10	2019/9/2 16:08:49	1899	30	100173
JG02	2019/9/2 15:41:46	2019/9/2 16:00:16	1110	38	113250

(b)

Fig. 4 Data preprocessing process
(a) Before processing; (b) After processing

4.2 Information level

Fig. 5 depicts the automatically generated and visualized VSM. The data box of VSM is redesigned, including the material arrival time, departure time, task card arrival time, and swiped time, which can represent the status of the entire production site at a given time. For better readability, only the key information for developing the required VSM is illustrated in the data box.

In this workshop, materials and WIPs were handled by batch, which was therefore used as the tracking reference in VSM. Values to represent the status of machine, materials, personnel, and task card are shown in Table 3. These data support reasoning in root cause analysis.

VSM is generated gradually along with the production: for example, at time 14:18, the workshop was processing panels for a filing cabinet and a supervisor's desk (Fig. 6). The filing cabinet is composed of a top panel, a bottom panel, and side panels, labelled as Batches A, B, and C, respectively. The supervisor's desk of table-board is composed of two panels, labelled Batches D and E. Batch A normally finishes processing on the grooving machine number 2. As the dash-line boxes in Fig. 5 indicate, a worker comes to grooving machine number 1 at 13:30 to prepare for Batch B and discovers the machine is in failure. This leads to the data box displaying 0:00. The worker leaves the station and calls for maintenance service at 13:36. VSM also displays that Batches D and E are processed on the sealing side machine 1 and the cutting machine 2 at 14:18.

After VSM visualization, data are further analyzed. Taking the utilization rate of a drilling machine as an example, Fig. 7 (p.391) illustrates the accumulated processing time and idle time at different periods, and the corresponding utilization rates. This information instantly reveals potential loss or problems, and prepares managers for an improvement activity.

Other instant causes have been identified based on statistical data analysis, such as work-in-process inventory or waiting time being excessive, but this is still insufficient to support decision-making on how to solve these problems.

4.3 Knowledge level

The information is then processed in the knowledge layer, utilizing the algorithm, rule, and lean knowledge bases. In this case, a decision tree algorithm was used to investigate the root cause of a low machine utilization rate. The procedure used is outlined as follows. First, the existing root causes for the low utilization rate of the drilling machine that relate to the actual status of production were aggregated in advance. In Table 4 (p.391), A=1 represents that the value of processing end time of material type N minus second processing started time of material type N is greater than the reasonable time interval. B=1 represents that the value of processing end time of material type N−1 minus arrival time of material type N is greater than the reasonable time interval. C=1 represents that the value of processing end time of material type N−1 minus swiping time of task card type N is greater than the reasonable time interval. D=1 represents that the mode changing time is greater than the reasonable time interval. E=1 represents that the value

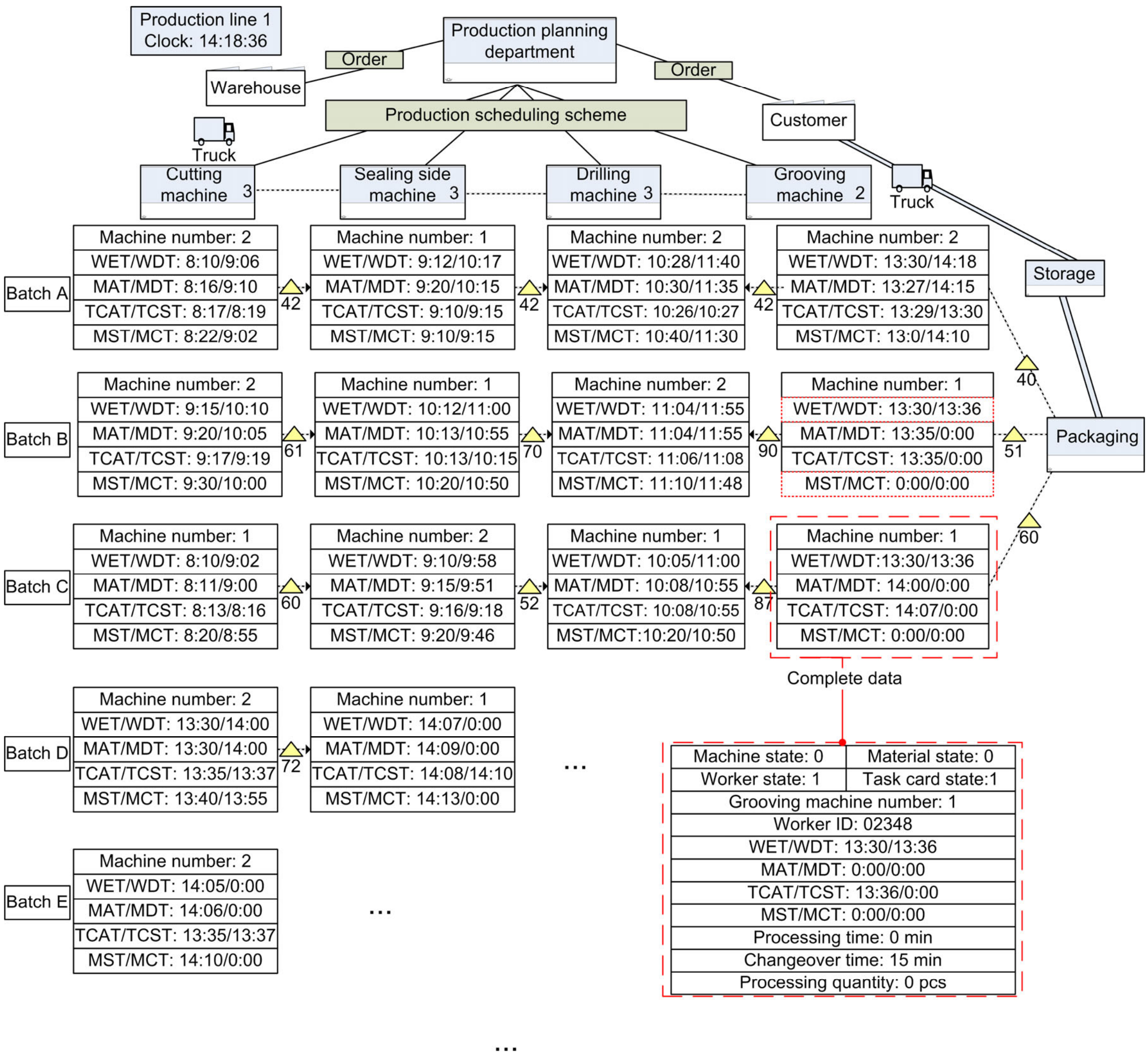

Fig. 5 Developed VSM

WET: worker entry time; WDT: worker departure time; MAT: material arrival time; MDT: material departure time; TCAT: task card arrival time; TCST: task card swiped time; MST: machine start time; MCT: machine completion time

Table 3 Values for different statuses

ID	Status			
	Machine	Worker	Material	Task card
0	Idle	Not in the station	Not in the line side inventory area	Not being swiped
1	In processing	In the station	In the line side inventory area	Being swiped
2	In failure	–	–	–

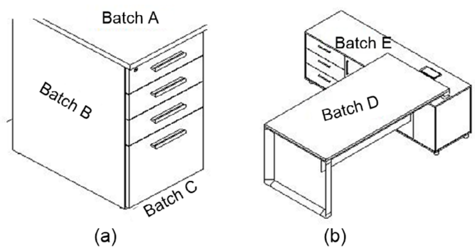

Fig. 6 Processing product

(a) Filing cabinet; (b) Supervisor's desk

of processing started time of material type N minus swiping time of task card type N is greater than the reasonable time interval. Second, the corresponding decision tree was generated based on a classification and regression tree (CART) algorithm. The pseudo-code of the algorithm is given in the Appendix A.

The generated decision tree is illustrated in Fig. 8a. For example, when the status of materials, workers, and task cards shows (1, 1, 1) respectively, the most-likely root cause ID is 7. Besides, a new issue could be discovered and its root cause will be renewed. For example, when a new status (0, 1, 1, 0, 1, 0, 0, 1) pops, the algorithm will report an error. After its root cause is identified, a new branch will be added dynamically to the decision tree (Fig. 8b).

With the data streamed from the smart furniture production workshop, the root cause of the low machine utilization rate was automatically mined and

Table 4 Root causes in relation to the furniture production status

ID	Worker status	Material status	Task card status	*A*	*B*	*C*	*D*	*E*	Root cause ID	Root cause
1	0	0	0	0	0	0	0	0	1	Normal
2	0	0	1	1	0	0	0	0	2	Long backflow time
3	0	0	1	0	0	0	0	0	3	Wrong task card delivery
4	0	1	0	0	0	0	0	0	4	Wrong material delivery
5	0	1	1	0	0	0	0	0	5	No worker in station
6	1	0	0	0	0	0	0	0	6	Unfamiliar with operation
7	1	0	1	0	1	0	0	0	7	Delayed material delivery
8	1	0	1	0	0	0	0	0	8	Unreasonable time interval setting
9	1	1	0	0	0	1	0	0	9	Delayed task card delivery
10	1	1	0	0	0	0	0	0	10	No task card swipe
11	1	1	1	0	0	0	1	0	11	Low efficiency of the mode changing
12	1	1	1	0	0	0	0	1	12	Inconvenient manual panel loading
13	1	1	1	0	0	0	0	0	8	Unreasonable time interval setting

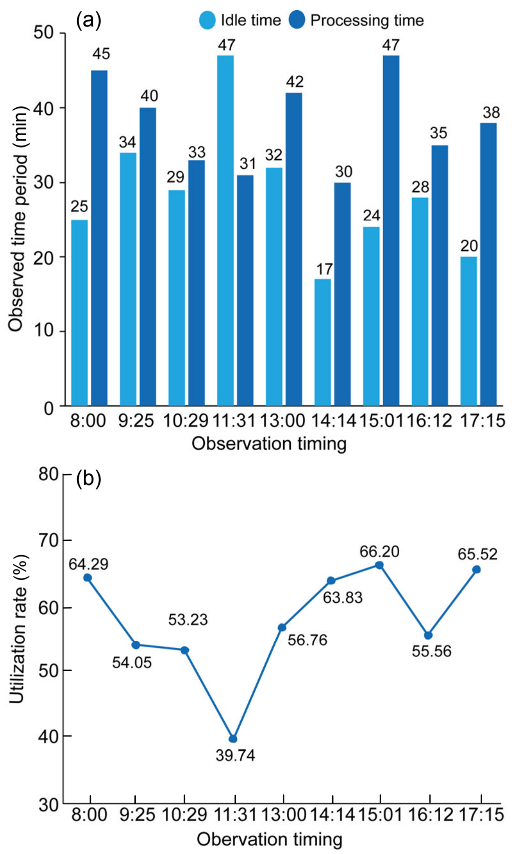

Fig. 7 Drilling machine utilization statistics
(a) Time statistics; (b) Drilling machine utilization

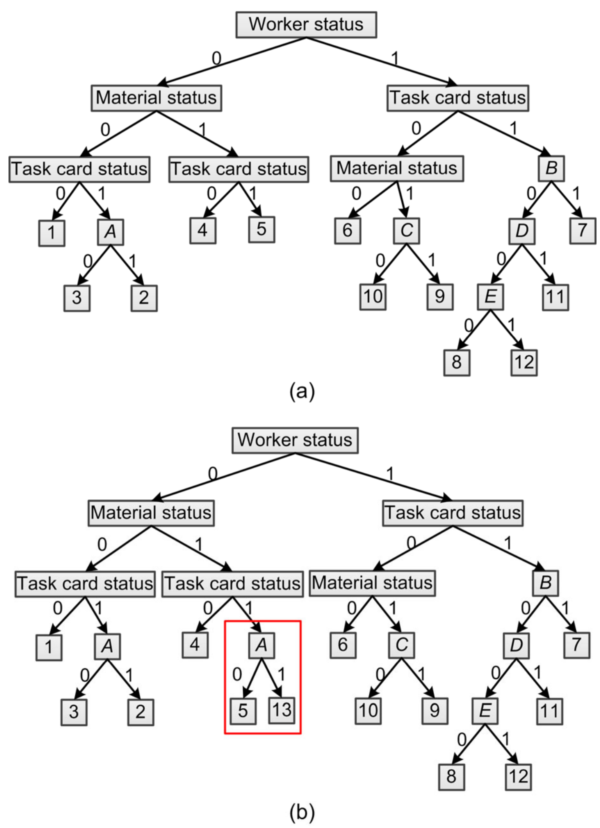

Fig. 8 An example of decision tree generation and update
(a) Originally generated decision tree; (b) Updated decision tree

presented to the operator via a user interface (Fig. 9) to assist a timely response.

The identified root cause of the low machine utilization rate was inefficient material loading, which was fed back to the production department to design an automatic fixture. Two fixtures were fabricated the next day and placed in the loading bay of the drilling machine. From the third batch onwards, the average loading time saved was 12 s. In this way, the issue was solved within 2 d, which was considered efficient compared to the 7-d production cycle. The designed fixture is shown in Fig. 10.

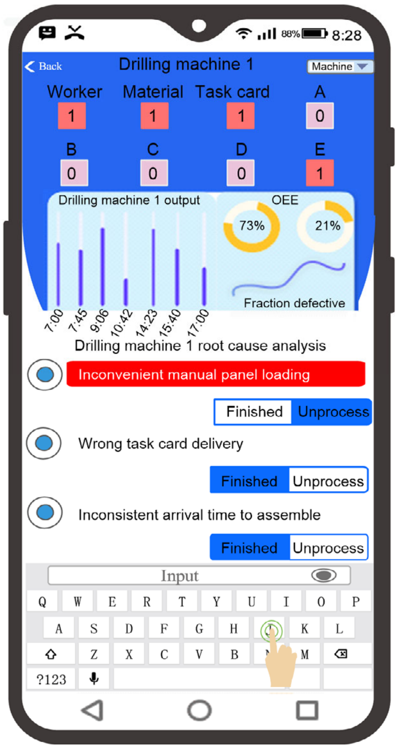

Fig. 9 A prototype system with user interface

Fig. 10 Automatic fixture

5 Conclusions

Advances in ICTs accelerate the transformation of manufacturing in Industry 4.0 by enabling data collection and exchange anytime anywhere, providing manufacturers with a new and important form of asset, data. How to mine the data, extract the information, and form knowledge in a timely fashion has been the most challenging task. Lean production tools, in particular VSM, have been shown to be useful in practice, and need to incorporate this data. The literature reviewed here suggests that there have been few studies on how to improve the efficiency of VSM to assist decision-making in such a data-rich environment. Therefore, in this paper we propose a systematic framework of automated VSM to rejuvenate lean production tools in the Industry 4.0 era. An implementation case of a furniture manufacturer in China is introduced to help readers better understand the framework.

This paper makes several contributions. Firstly, the framework proves that it is feasible to incorporate Industry 4.0 technologies to improve the efficiency of traditional VSM. Other lean production tools can follow this framework for reliable and efficient decision-making. Secondly, it provides a roadmap to help enterprises integrate Industry 4.0 technologies and lean production tools to achieve a higher level of manufacturing performance and competitiveness. Thirdly, it shows that traditional VSM can make full use of production data to cater for multi-varieties and small-batch production, with timely on-site waste identification and automated root cause analysis. There are some limitations: the process from lean production tools to solution still requires operator intervention and is not yet automated. The lean production tools recommended for Industrial 4.0 technologies need to be further explored. In future work, the framework will be applied in smart workshops to verify its effectiveness in different production situations.

Contributors

Hao-nan WANG: investigation; formal analysis; methodology; writing-original draft; visualization; validation. Qi-qi HE: methodology; data curation; investigation; validation.

Zheng ZHANG: methodology; resources; investigation. Tao PENG: conceptualization; writing-review and editing; supervision. Ren-zhong TANG: project administration; resources; funding acquisition; supervision.

Conflict of interest

Hao-nan WANG, Qi-qi HE, Zheng ZHANG, Tao PENG, and Ren-zhong TANG declare that they have no conflict of interest.

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Appendix A: pseudocode for the CART algorithm

Algorithm: Generate_decision_tree (training samples, attribute)

Input:

training samples

attribute_list=[‘Worker status’, ‘Material status’, ‘Task card status’,

‘End time of material N processing−Second started time of material N>Reasonable time interval’,

‘End time of material N−1 processing−Arrival time of material N>Reasonable time interval’,

‘End time of material N−1 processing−Swipe task card N time>Reasonable time interval’,

‘Time of the mode changing>Reasonable time interval’,

‘Material N processing time−Swipe task card N time>Reasonable time interval’]

Output: decision tree

Create node N

```
if samples are all in the same class C:
    N as the leaf node and mark as class C
    return decision tree
end if
if attribute_list==ϕ:
    N as the leaf node and marked as the most numerous class
     in class C
    return decision tree
end if
Calculate and select the attribute that has the lowest Gini in
     attribute_list and name it as best_attribute
name n as best_attribute
For each possible value a_i in best_attribute
    The sample is divided into several subsets according to
     best_attribute=a_i and name as s_i
    From node N grows a branch with the condition
     best_attribute=a_i
    if s_i==ϕ:
      Branch node as the leaf node and marked as the class
       with the most samples
      return decision tree
    else
      Take the branch node returned by Generate_
       decision_tree (s_i, attribute_list-best_attribute)
       recursive invoke to the above process
    end if
end for
```