Kanban system based on manufacturing equipment operation monitoring

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Abstract. This work paper presents a single-channel Kanban solution where ticketing from downstream operator to the upstream operator in production flow is automatically performed when the completion of operations is identified. Thus, a more efficient transmission and placement mechanism for the tickets is provided for real-time operation of the machines, compared with others Kanban solutions. Our proposed solution contains elements of modern interdisciplinary research: industrial process improvement solutions using one Just in Time methodology: Kanban system, self – harvesting sensors, non-invasive monitoring solutions, multiple-source acquisition software, complex event processing and real-time parallel processing, use of Machine Learning analysis techniques (Deep Learning networks) to identify equipment operating regimes, use of ad hoc radio networks for data communication. The system was developed at an experimental model level. The article presents, with results, a case study in which we have two operators in a production stream. As will be shown, the system has a high degree of scalability, so it can easily be extended to any number of operators in the production stream.

1. Introduction
The system presented in the paper allows the implementation of a single-loop Kanban production flow management. The difference to a standard implementation is that tickets are automatically generated by detecting current consumption and identifying some equipment operating sequences in both downstream and upstream production processes. The system is a result of interdisciplinary research: non-invasive systems for monitoring current consumption with wireless data transmission, identification of the operating regime of industrial equipment by intelligent analysis of the electricity consumption variation over time, the use of a client-server computer system based on complex event processing and, of course, implementing a Kanban system to optimize production flow in the automotive industry – in this case two industrial processes in the chassis production.

The Kanban system, one of the most important components of Toyota Production System (TPS), is a simple and effective tool to accomplish the pull concept of lean manufacturing [1]. A Kanban system is one of the important elements of Just-in-time (JIT) philosophy [2]. Kanban means card in Japanese. In a Kanban system, cards are used systematically to control the production within stations and the movement of parts between stations. It is used to effectively control work-in-process (WIP) inventory.
In the production and operations world, there exist various types of Kanban and optimization approaches. The original concept of Kanban has four components: (1) use of two communication signals (dual card Kanban system), (2) pulled production, (3) decentralized control, and (4) limited WIP [4].

Due to the technological evolution, the automatic AC monitoring systems have become extremely flexible and efficient. Thus, we have sensors that allow the acquisition of current consumption by analyzing the electric field around the isolated conductor [5]. These technologies allow for power consumption monitoring without the need for power cable interventions. The sensors are placed as clamps on the isolated cable. They allow the acquisition of AC power consumption from 2A to 600A. On the other hand, with the manufacturing technology, sensors require very low power consumption; therefore, they can be integrated into low-power solutions with a high degree of energy autonomy.

At the same time, energy sources have been developed for low-consumption integrated systems that allow the acquisition of electricity from other renewable sources: the most "conventional" such as solar (photovoltaic panels) or wind power, but also by using mechanical energy from industrial machines [6] or by using electric fields radiated by conductors or transmission stations [7]. Such a source, together with a sensor integrated system, forms a "self-harvesting" solution able to obtain the energy required for the operation itself.

In the Internet of Things era, radio communications have also evolved into solutions that enable - through low-energy consumption - data to be transmitted through hardware technology but also through communication protocol [8]. Such solutions can be integrated into low power acquisition "self-harvesting" systems. Such a solution will be used to acquire power also for our system. The data centralization from the IoT systems used in more and more domains, including the industrial environment [9], is done through server-based IT applications specializing in complex event processing. Thus, they can retrieve data using various communication protocols, including those specific to the industrial environment, they can process these data in real time by applying filters, comparisons, etc., they can store data in different database systems, and they can operate intelligent techniques analysis of stored data and can generate dashboards or reports where processing results can be viewed. Such an application can be used to acquire current consumption over a period of time, its intelligent analysis and determining an operating mode of the equipment that determined the respective consumption. In our case, the determination of this regime is used to identify the stage in which a part is processed both at the downstream and upstream point of the industrial production flow.

Currently, there are several commercial solutions that use a Kanban computer system. Further research is being done to achieve more effective implementations [10] or through improvements applied to algorithms [11], including through the use of artificial intelligence [12].

The original element brought about by our solution consists in the method of generating tickets: by analyzing the operating regime of the equipment that process the parts. This is a solution for automatically generating Kanban tickets. Unlike other methods of automatically generating tickets: barcode or RFID, our solution does not involve any additional operator intervention. Using barcodes, for example, involves applying them to a piece/car part (so it is done by an operator), but reading them with a reading device.

More efficient would be an RFID system where tagging is done by an operator and reading is done automatically when the piece is passed through a workspace (where, of course, there is an RFID reader). However, this solution also has a problem when the processing action involves the entire part. For example, cataphoresis involves sinking the entire part into a colloidal solution - a process in that an RFID tag is unlikely to resist. Instead, our method does not involve placing any tags on the part (or on a parts container). It simply starts from a non-invasive analysis of the operating regime of the downstream processing equipment or upstream of the production flow. If this mode of operation indicates the completion of the downstream stage, this is equivalent to issuing a ticket towards the upstream production flow.

Also, if an upstream operating regime is indicated, this is equivalent to issuing a ticket. Our system has been experienced for two stages in the chassis production flow – that is for large pieces,
i.e. car components - each piece having a Kanban ticket. Of course, it can also be implemented for batches of parts, in which case the operating mode of the equipment for the production of a part batch will be identified. The solution can be improved by monitoring the route between the two work-station points, e.g. monitoring the transport line between the work-station points.

2. System description
The overall block diagram of the system is shown in the figure below.

![System block diagram]

**Figure 1.** System block diagram.

The following components can be identified:
- the non-invasive monitoring module of the machine current consumption. It is based on a clamps sensor that determines the current consumption by acquiring the electric field around the insulated conductor powering the equipment. Also, the monitoring module has a wireless data transmission stage. Both the sensor and the data transceiver are made with low power technologies. That's why the whole module is powered by a source that uses the energy captured by the sensor coil (self-harvesting solution). Thus, when the equipment consumption exceeds 2A, the module has energy independence and it can acquire and transmit data at a rate of 0.5Hz (at 30 seconds). Other features of the module are: 220V mono-phase or three-phase 380V, 50Hz, 2A - 600A alternating current/AC, low power radio communication, 866MHz (free band), maximum coverage 20m. It is placed on the isolated power supply of the equipment, so it does not require any intervention on the equipment.
- the centralizing node is the module responsible for collecting data from the monitoring modules placed within a node - for example, a work-station. Collected data is transmitted wirelessly to the server. For communication with the server we chose an Xbee protocol in the 2.4GHz free band, with a coverage area of up to 2km. So, as can be seen in the figure, the communication between the central nodes and the server is through a second local radio network with a larger coverage area. As node
parameters: it supports up to 15 monitoring modules on a maximum of area of 20 m, it encapsulates
data in packets in which we have the ID for each monitoring module, current values, and the time at
which the data was received. At the same time, the centralizing node attaches its own ID. So we have
several node networks for each work-station and an enterprise network at the factory level.

- The Level 1 Server handles the data acquisition from the centralized nodes (through the Xbee
gateway) and the data storage. It makes a real-time correlation of the data received based on the ID.
Thus, it builds a time evolution of current consumption from a particular equipment within a
centralizing node.

- The Level 2 Server determines the equipment's operating regime based on an intelligent analysis
of the power consumption evolution over time. Specifically, for each equipment, it identifies patterns
that the equipment consumes when operating and finishing the work upon the processed part. An
alarm for the level 3 server will be generated when the operating mode is detected.

- The Level 3 Server interprets the Level 2 alarms as releases - ticket allocations. Thus, an alarm
generated at the downstream work-station signifies the transmission of a production Kanban ticket
while an alarm generated at the upstream work-station means the (virtual) allocation of a Kanban
ticket for a piece to be stored. Here also takes place the display of the visual array - it will be done
through a client web interface.

The server can receive 5,000 packets of data per node / minute. It uses, for storage, a database with
an ultra-fast search engine. For the intelligent recognition algorithm, a deep learning and predictive
learning neural network is used. It also allows - on a graphical user interface (dashboard) - the display
of the visual array with Kanban tickets.

2.1. Deep learning neural network

As we have shown, at the level 2 server, the working process identification takes place by analyzing
the evolution of current consumption over time for each equipment separately. For this we used a deep
learning neural network. The explanation for this choice lies in the requirement to identify - from the
evolution in time - the current consumption of certain patterns indicating the operating mode -
operating mode finalization.

As it can be seen in the figure, in an operating mode, some differences in the profile of the
consumption evolution may occur, differences resulting from the appearance of some parasites in the
network, which is very possible due to the power equipment available in an industrial environment,
but also as a result of other factors that may affect consumption. The idea is to recognize the pattern
even with these differences that may occur.

It is also necessary to identify the operating pattern and the finalizing pattern of operation, which is
differentiated from other operations that can be done with equipment - such as testing or maintenance
works. It results from these requirements that an algorithm is necessary not only to apply a "matching"
identification for a certain evolution of consumption but one that could learn to recognize certain
patterns. For this, an intelligent learning and intelligence algorithm is needed: i.e. a neural network.

The structure of the neural network we have used is shown in the figure 3.

Consequently, it was chosen a Deep Learning Neural Network with 60 neurons in the input layer
(for our experiment, the equipment operating time averaged 30 minutes), 128 in the hidden layer, and
5 in the output layer. The five output classes are: pattern recognition of operation – operation
completion equipment 1 node 1, pattern recognition equipment 2 node 1, pattern recognition
equipment 1 node 2, pattern recognition equipment 2 node 2 and other operations.

The Keras / TensorFlow libraries were used for implementation. The optimization method chosen
was RMSprop. The activation function for the input and the hidden layer is Relu \( f(x) = \begin{cases} x & x > 0 \\ 0 & \text{otherwise} \end{cases} \) and sigmoid (softmax) for the output layer.

The system allows learning different consumption patterns, for different equipment at the same
work-station or at different work-stations. It is flexible: changing the equipment involves re-training
the neural network.
3. Experimental results
The figure below shows the industrial process where the system was experienced. The parts manufactured are chassis, so large parts, each having a Kanban ticket. We have two nodes, each with two manufacturing equipment: one upstream node and one downstream of the production stream.

Upstream (node 1) we have a welding process that applies to two different chassis types (here are represented with one circle and the other with a square). Further downstream, we have cataphoresis for the two chassis types. Storage capacity between the upstream and downstream process is minimum 2 and maximum 5 for the first chassis while for the second is minimum 3 and maximum 7. The
minimum capacity means that in order to guarantee a continuous production stream it is preferable to have a buffer stock of at least 2 chassis type 1 and 3 chassis type 2. The experienced system allows at one time the operation of only one equipment node (welding or cataphoresis).

The implementation of our system involved three steps: deployment, training and operation.

Figure 4. System utilisation in a real manufacturing process.

3.1. Deployment
4 monitoring modules (placed on each equipment), 2 centralized nodes, 1 server (Intel i7, 2.7GHz, 32GRAM, SSD 256G, HDD 1T) were used. The placement of the monitoring modules was done without any intervention on the equipment infrastructure. They were placed on the power supply of the welding transformer and on the cataphoresis crane feed. The nodes were placed around the monitoring modules with power from the low power (220V) power network. The server has been installed in the management and quality control centre. The power supply for the server was provided from the low power grid.

3.2. Training
In the first phase, 4 acquisitions x 30 minutes were performed each during the operation and completion stage of each equipment. These will be used as training templates. Two other acquisitions x 30 minutes / equipment were used as test templates.

With these templates, a supervised learning algorithm has been applied. The results are presented below.
As we can see in the listing, in 20 epochs of about 3 seconds each the training was done with 97% accuracy in the recognition of the patterns.

3.3. Operation

It is the phase in which the system's effectiveness with the learned paths has been tested. Now data provided by the nodes is transmitted to the server where it is stored and classified using the neural network. If the patterns are recognized, they generate alarms that are converted into Kanban tickets, as shown in the previous section.

The charts below show the progress of parts production in the production flow for each equipment over a 24-hour range. The charts are compared to the production of parts without the use of the system (the parts were produced until the maximum storage capacity was reached, and there was no immediate feedback when the downstream equipment was emptying the time deposit).

The rising slopes in charts indicate upstream activity that increases the number of items in the warehouse, the falling slopes indicate downward activity that decreases the number of parts in the warehouse and stagnation in time is caused by breaks taken by crew or switching tours (8 hours change the tour, 4 hours is the break). The table below shows the results obtained with the existing classical and Kanban system.

As it can be seen, a first effect is to increase production efficiency. Thus, using the classic planning, we have 15 Type A and 16 Type B pieces, while with the Kanban operating system we have 19 pieces of both types. It can be seen in the table also the number of half-hours of activity for the welding / cataphoresis teams for the three work shifts. The Kanban method leads to a slight load for the first work shift, when it takes place the warehouse loading, then the effort on the staff is the same as the classic planning! This is because, using the Kanban method, staff are no longer required to carry out activities on a long-term basis.

Along with increasing efficiency through the use of a Just-in-Time system, an effect felt when integrating the system was the improvement in the maintenance planning. Thus, without the system the maintenance activity could only be planned after a cycle of about 150 minutes of continuous operation for the equipment from both nodes to the A-type parts. On the other hand, by using the Kanban method, maintenance activities can be planned at shorter time intervals: 90 or even 60 minutes. Things are similar for the B-type parts.
Figure 5. Evolution of number of parts in warehouse between upstream and downstream process. The rising slope represent activity in upstream node and falling slope activity in downstream node. With blue is evolution using previous classic method and with orange Kanban method implemented with our system.

Table 1. Results obtained with classic and Kanban implemented with our system production flows.

| Finished Parts | Switch 1 man per ½ hours welding/cataphoresis | Switch 1 man per ½ hours welding/cataphoresis | Switch 1 man per ½ hours welding/cataphoresis | Part type and production flow |
|----------------|---------------------------------------------|---------------------------------------------|---------------------------------------------|-----------------------------|
| 15             | 7/5                                         | 7/5                                         | 7/5                                         | Type A classic              |
| 16             | 7/6                                         | 7/5                                         | 7/5                                         | Type B classic              |
| 19             | 9/5                                         | 7/7                                         | 7/7                                         | Type A Kanban               |
| 19             | 10/4                                        | 7/7                                         | 6/8                                         | Type B Kanban               |

4. Conclusions
Using a JIT Kanban system to improve the production flow has long been a thing that has been accepted and implemented in the industry. However, problems arise as to how such a system is being implemented. It usually involves the existence of operators who have to devote their time to carrying out tasks specific to the Kanban usage (labeling, transmission of labels). For this reason, it has been attempted to automate the placement and transmission of tickets by implementing computer and hardware systems. Our solution totally solves this problem. By monitoring the evolution over time of the power consumption of the equipment, we can automatically determine its operating status.

Thus, we find out indirectly what is the "position" of the parts in the production stream. In this way, production tickets will be automatically issued from the downstream work-stations to the upstream work-stations. Also, by identifying the working regime of the upstream machineries, practically it can be considered the labeling procedure (virtually of course) of the parts that go further into the production stream.

As future research directions, we see experimentation with more than two nodes - implementation of the system and some intermediate nodes that include transport (logistics) and storage between two work points.

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