Improving scheduling methodologies in a Hot-Dip Galvanizing Line combining non-linear projectors and clustering

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***Abstract*—An improving methodology for the scheduling coils of a Hot Dip Galvanizing Line (HDGL) is presented. This method uses a non-linear projector which has been selected from various techniques to generate a coil map from the most significant parameters of the coils database: process variables, chemical composition of steel, measurements, etc. The created bidimensional map helps experts to decide which are the more fitting groups showing the distances between all coils. After that, the expert can select with an end-user application one group and identify other coils that can complicate the scheduling purposes. Finally, the methodology uses hierarchical clustering to obtain a list of effective sequences of coils. A decrease of the number of shutdowns and irregular heat treatments failures can be obtained by using this scheduling method.**

***Index Terms*—Scheduling Methodology, Hot Dip Galvanizing Line, Hierarchical Clustering, Sammon Mapping, Kruskal's non-metric projector**

I. Introduction

THERE The constant effort to increase product quality [27] and reduce the expenses caused by failures in the manufacturing process is ongoing with Hot-Dip Galvanizing Lines, which are always trying to optimize their operative costs.

A. Hot Dip Galvanizing Line

This industrial process is composed by several stages. The initial material is the steel coils from the cold rolling with the required thickness.

Broadly speaking, the process within a Hot-Dip Galvanizing Lines (HDGL) (Figure 1) can be described in the following manner: The first stage in the line consists of the formation of a continuous strip using steel coils that come from a mill process. Next, the strip passes through a preliminary cleaning section at the entrance of the annealing furnace, where it receives a heat treatment; the stage prior to its immersion in the liquid zinc bath. This treatment is essential in order to improve the properties of the strip and its coating. After the bath, the strip exits vertically, passing through blade-like currents of air which regulate the thickness of the cover. The temperature and cooling rates are controlled to obtain the desired mechanical properties for each steel type.

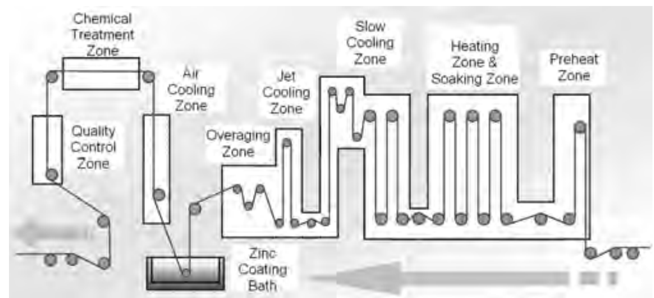

Figure 1. Basic scheme of a HDGL

Finally, the steel is run through a molten-zinc coating bath, followed by an air stream wipe that controls the thickness of the zinc finish (see Fig. 1). This description, with minor modifications, is valid and applicable to all Hot Dip Galvanizing Lines in operation throughout the world.

B. The Quality of the Galvanized Product

The quality of the galvanized product, according to several authors [2], [19], can be divided into two fundamental aspects: the anti-corrosive characteristics and the properties of the steel.

First, the anti-corrosive characteristics: steel comes marked by the thickness and uniformity from the zinc coating and basically depends on the superficial preparation of the metal bases, the control of the heat treatment, the bath composition and temperature, the air-blade control, the speed of the strip and the amount of time available for alloying at the specified temperature after the air-blade treatment.

Secondly, the properties of the steel which fundamentally depend on the composition of the steel, the surface roughness, the process of smelting, the processes of rolling and finally,

Manuscript received January 31, 2011: Revised version received March 8, 2011. This work was supported in part by La Rioja University through FPI fellowships and the Autonomous Government of La Rioja under Grant FOMENTA 2010/13.

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the heat treatment that is applied to the strip before its passage by immersion in the liquid-zinc bath.

By examining previously exposed coils, it can be deduced that the control of the heat treatment in a HDGL is fundamental for the process of coating and for the improvement of the properties of the steel. One of the key aspects concerning temperature control consists in assuring that the suitable thermal cycle is reached for each coil while considering the limitations of the HDGL furnace inertia. This is fundamental for the process of coating and for the improvement of the properties of the steel and can only be accomplished when the flow of the steel mass for unit of time is constant and the changes therein are carried out gradually. A fundamental coil sequence constraint is the need to limit changes in the mass flow rate from one coil to the next. But we must also examine other inconveniences. For example, coils within each group have to be sequenced based largely on decreasing sort by width or coils that have to be selected with similar steel properties and thermal requirements.

Also, it must be borne in mind that defective coils can appear, or coils with characteristics that differ greatly from the others, and therefore, must be separated from the rest. For these reasons, it is crucial to order the coils that form the strip in such a way that the varying thickness, widths and types of steel do not differ too greatly [23], [31]. When this is accomplished, the temperatures generated by the furnace progressively fit each individual coil.

We see, therefore, that one of the most important tasks in the process in an HDGL is centered on obtaining sequences of coils that do not contain abrupt changes in the dimensions and types of steel in the consecutively treated coils. Logically, depending on the type of process, the demands of planning will be different.

As has been mentioned above, one of the primary aims of the HDGL is to determine the best sequence of coils, after which it conforms to the changes in the new dimensions and types of steel. This is essential in assuring that the quality of the coating of each coil and the production are optimal.

The present systems of planning in the HDGL divide the process into two general phases:

- The coils are grouped according to the type of steel (depending on its chemical composition) and its specifications (specifications of production, date of delivery of the product, specifications of quality, etc.).
- Each group of coils is ordered such that the changes in width and thickness are minimalized. Normally, the process of coil scheduling begins by selecting those coils of greater width, and gradually moving towards those that are more narrow. Also, the HDGL looks for variances which are minimal, so as to create a smooth transition.

II. Previous Work

We review some of the present scheduling [4], [25] techniques in steel industry. There are several publications that deal with the problem of scheduling in an HDGL. The majority of the publications that address applications and techniques for scheduling in the steel industry are based on continuous casting machines. The systems presently employed in these processes are generally based on either heuristic scheduling strategies or are implemented using knowledge software technology [23], [26].

Tang et al. [31] offer a review of the more commonly used methods and scheduling systems in the steel industry. In this work, different methods of optimization are described according to many planning systems (actually integrated in several industrial plants in the steel industry).

In this article, the optimization techniques are grouped according to the following classification:

- Mathematical or heuristic models extracted directly from the analysis of the process.
- Methods [11] of artificial intelligence (AI) divided as well into: a) Expert systems: based on the experience of the experts and the observed process restrictions. b) Random methods in search intelligence: genetic algorithms (GA), simulated annealing (SA) and tabu-search algorithms (TS). c) Constraints satisfaction methods (CSP) [32].
- Human-machine coordination methods: consisting of the creation of scheduling by means of the iterative dialogue between human and machine.
- Multi-agents methods (A-teams methods): which rely on the cooperation of multiple models with different algorithms (each one of them with different constraints), so that the best solutions are found [10], [15].

For each kind of problem, multiple mathematical approaches and heuristic algorithms of optimization are selected [18], [29]. Other authors [9] focus the resolution towards problems of the type Traveling Salesman Problem (TSP) using the dimensions of each coil and other parameters. This methodology is based on the calculation of a triangular matrix of distances between all the coils to determine the best possible sequence. The most critical point of this consists in finding a trustworthy formulation that indicates the degree of existing similarity between two coils according to their physical and chemical properties, as well as restrictions in the process.

Other works, however, are based on the use of graphical methods for scheduling. For example, Tamura et al. [28] looks for optimal ways in distribution maps where each coil is represented according to two coordinates: thickness and width.

At the moment, these techniques are complemented with new techniques [6][17], [20]: Prize Colleting VRP models, IA, multi-agents, methods of man-machine iteration, or combinations of all of the above.

Finally, other works study when scheduling problems are subject to unexpected events. In these cases, the steel plant needs a scheduling decisión that must be made in real time about the possible rescheduling or reordering of tasks. Recently years, new scheduling techniques, as known as hybrid dynamic scheduling systems, have been developed por solving this hard problem. Aytug et al. [1] used an evolutionary algorithm to modify an initial knowledge base, using results taken from the simulation of the manufacturing line. In that contribution they achieved that the system could react to unexpected events. Ikkai et al. [13] proposed a status selection method based on evolutionary algorithms to induce scheduling knowledge from manufacturing lines.

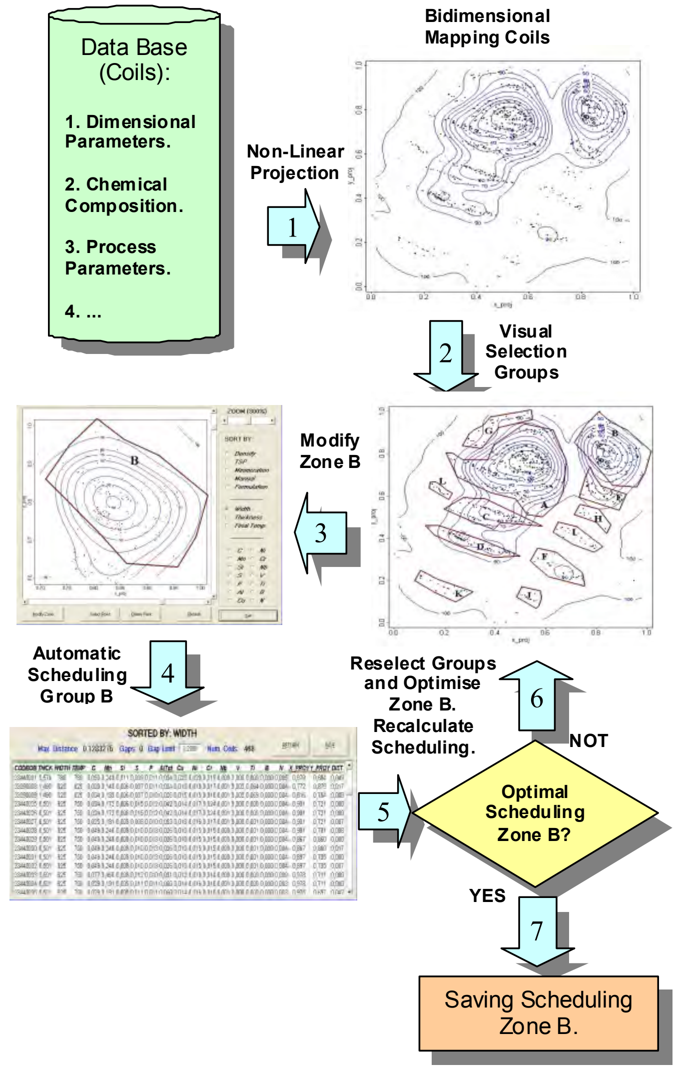

Figure 2. The diagram of the complete methodology

In this work consists of a several-step approach to the problem using multi-dimensional scaling and hierarchical clustering. In the following sections, another experience is described, results obtained are discussed and final conclusions are drawn.

III. Methodology

The methodology that considers in this work, consist of an approach to the problem in seven steps. Figure 2 presents the complete and comprehensive flow chart explaining the proposed methodology to select the optimal coils scheduling sequence.

The first step consists in developing a data base with the n weighted parameters of each coil (considered important within the classification process). These parameters are the followings:

- Width and thickness of the coil.
- Objective temperature at the process.
- Chemical composition of the steel (C, Mn, Si, S, P, Al, Cu, Ni, Cr, Nb, V, Ti, B, N, Ceq).

Second, the present work makes use of multidimensional scaling (MDS) for exploring similarities or dissimilarities in order to generate a bidimensional map of the coils and then, a clustering technique is utilized to find the local clusters. The clustering technique is able to reduce the amount of data items by grouping them, but projection methods are necessary to reduce the dimensionality of the data in the first place. In addition, the projection can be used to show groups if a enough small output dimensionality (two or three dimensions) is chosen.

A. Principal component analysis

This mathematical procedure is used to show a set of data as a linear projection [21] on such a subspace of the initial data space. This conversion is defined in such a way that the first principal component accounts for as much of the variability in the data as possible. This transformation is sensitive to the scaling of the initial data values and to outliers that produce large errors.

Table I
Importance of components for PCA

	PC1	PC2	PC3
Standard deviation	2.1394	1.6382	1.3419
Proportion of Variance	0.2692	0.1579	0.1059
Cumulative Proportion	0.2692	0.4271	**0.5330**

Thanks to the PCA and the knowledge based on expertise, it can be defined a set of uncorrelated and relevant variables (some chemical components of the steel). These are shown in Figure 3.

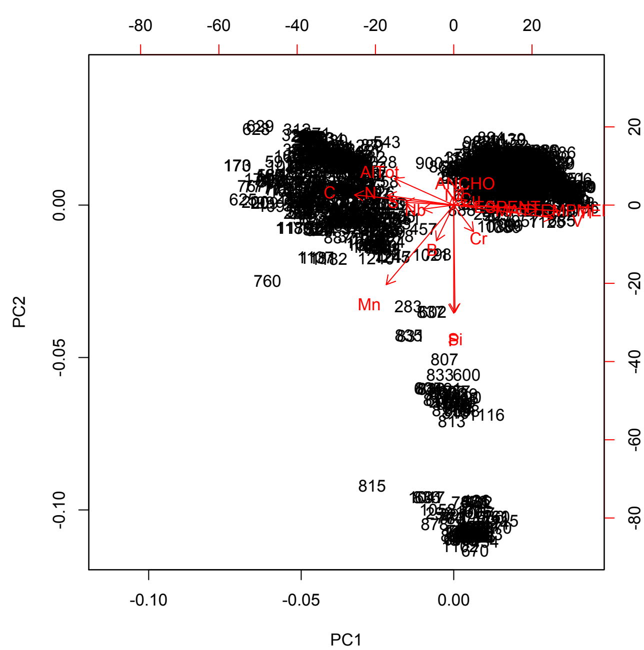

Figure 3. Coils data set with 17 main components

As shown Figure 4, the first three principal components (PCA1, PCA2, PCA3) doesn´t explain most of the coils groups

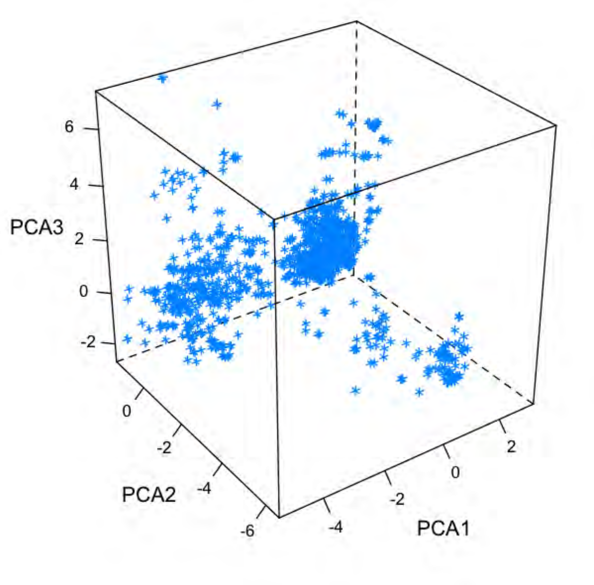

Figure 4. Tridimensional plot of the steel coils

in this work. Table I demonstrates that three principal axes of the PCA cover less than 55% of the cumulative proportion of variance, and therefore can not be used to project every of the coils.

It can be seen that the linear projection doesn´t work because , so we propose two alternative that does.

B. Kruskal's non-metric projector

This is another form of non-metric MDS method [5]. First, a n-dimensional configuration to minimize the stress is chosen. Then, an iterative algorithm is used, which will converge most of times in few iterations (about 10), but due the complexity of the algorithm this procedure is slow for large datasets.

Finally, this MDS uses the power for Minkowski distance in the configuration space, so results can vary considerably from one computer to another. Basically, the rank correlation between calculated dissimilarities and plotted distances is maximized, allowing tied distances to not have identical plotted distances, only sequential ranks. In Figure 5, the bidimensional map generated represents the distances between all the coils to organize.

C. Sammon non-linear projector

The Sammon non-linear projector [24] is suited for use in exploratory data analysis. In the present work, it is used to visualize the equivalent Euclidean distances [3] of the coils to be treated within a $\Re^2$ space.

This algorithm employs non-linear transformations in order to map the original space, from the significant n weighted parameters so that they can influence the classification process, onto a low-dimensional visual space ($\Re^2$ or $\Re^3$), attempting to preserve the Euclidean distances between coordinates of patterns (logically, other linear or non-linear multi-dimensional scaling methods (MDS) can be used) [8].

Let us denote the distance between two objects i and j in the space $\Re^n$ by $\hat{d_{ij}}$, and the distance between their projections by d_{ij}; Sammon mapping intends to minimize the error function known as Sammon´s stress:

$$E_i = \frac{1}{\sum_{i<j} \hat{d_{ij}}} \sum_{i<j} \frac{\left(\hat{d}_{ij} - d_{ij}\right)^2}{\hat{d_{ij}}} \tag{1}$$

The next step consists in reducing the original data base with the n parameters of each coil to the most important p parameters. These chosen parameters are the following:

- Thickness of the coil.
- Objective temperature at the process.

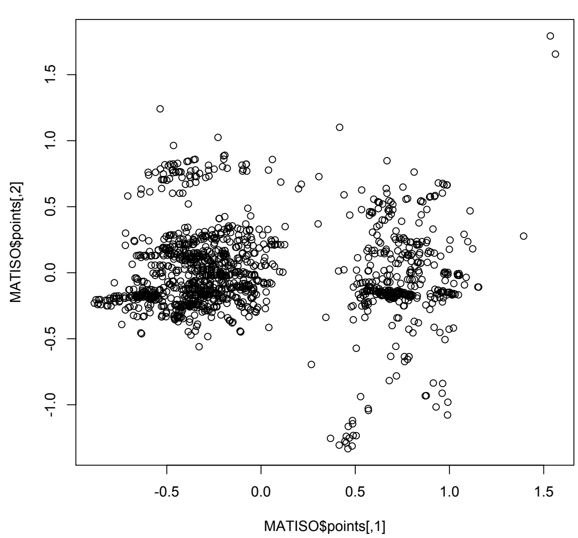

Figure 5. Bidimensional plot of Kruskal's Non-metric MDS

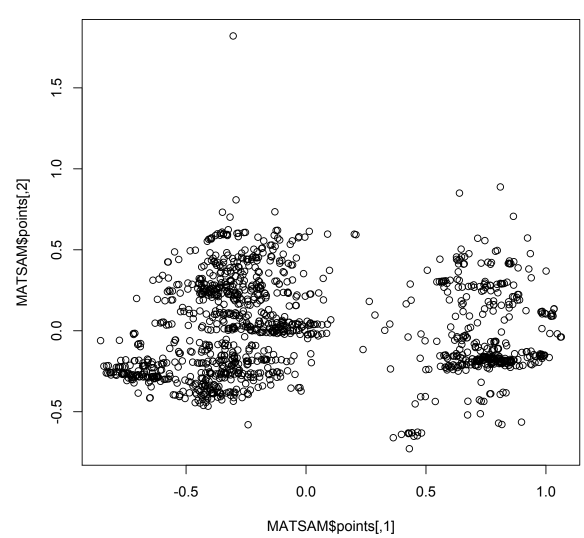

Figure 6. First bidimensional plot of Sammon's mapping

- Chemical composition of the steel (C, Mn, Si, S, P, V, Ti, B, N).

This new data set has better projection because there is only the most relevant variables for the first two axes of principal component analysis performed previously. In Figure 7, the final bidimensional plot of Sammon's mapping with the new data is represented.

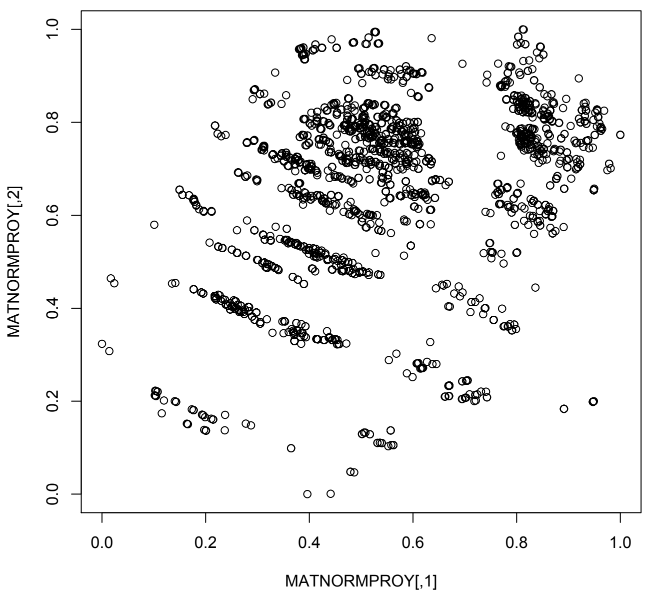

Figure 7. Second bidimensional plot of Sammon's mapping

D. Grouping of data

Once defined, the coils like points within a space $\Re^n$ are projected by means of Sammon projector in a bidimensional space. This bidimensional generated map represents the equivalent Euclidean distances between all the coils to organize.

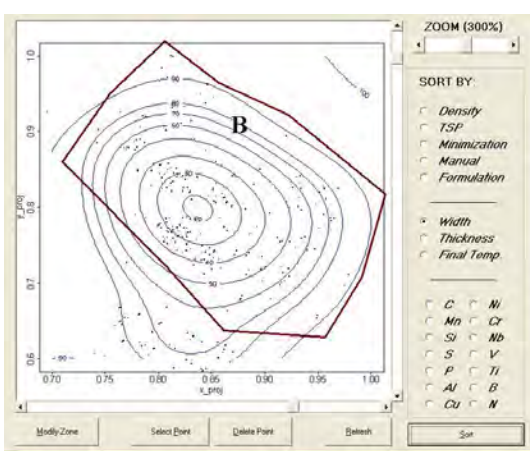

Figure 8. Defined groups visually using a Sammon´s map

In this way, the degree of similarity between the coils and the obtaining of the standardized distance of its projections can be determined visually.

This map of points allows one to visualize in an objective manner the equivalent distances between all the coils, and to classify them according to all the considered parameters properly weighted. Logically, the coils with very close parameters will appear tightly-packed, whereas those coils whose values vary greatly amongst themselves will appear more loosely-grouped.

Once all the coils in a two-dimensional graph have been projected, the integrated software system allows for iteration with a human expert for the selection of main groups of coils with similar characteristics (see Fig. 8).

From the map of coils generated with software package, the new groups of coils with similar characteristics are defined visually with a contour of lines that can be adapted by the user. Those different coils that do not correspond to any defined group are detected (Fig. 9).

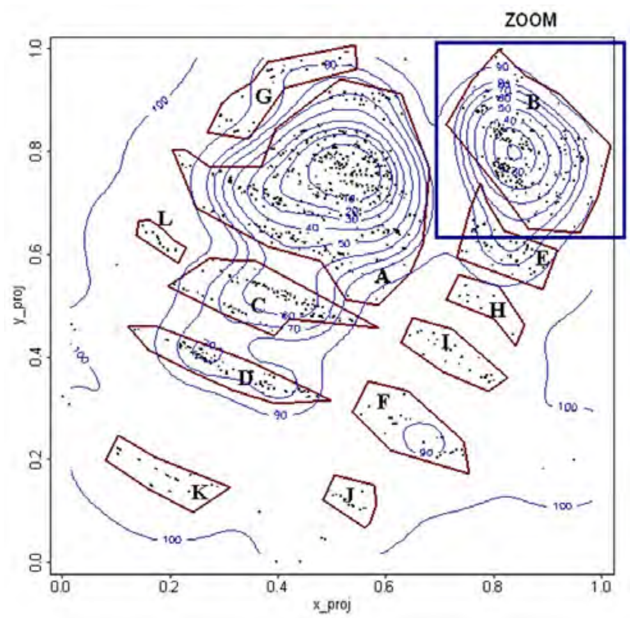

Figure 9. Defined groups visually using a Sammon´s map

E. Cluster analisys of data

When the main groups of coils are all selected, the coils of each group are locally grouped according to hierarchical clustering (see Fig. 10).

This is one of the large number of methods that have been proposed for cluster analysis. Presently, cluster analyses appearing in the literatures are mainly divided in four groups: hierarchical methods, optimal partitioning, distribution mixtures and non-parametric estimation of local densities. A strictly hierarchical method depends on dissimilarity or similarity measures, providing a complete scheme of division. This algorithm [14], [7] uses a set of dissimilarities for the n objects being clustered. Initially, each object is assigned to its own cluster and then the algorithm proceeds iteratively, at each stage joining the two most similar clusters, continuing until there is just one single cluster.

Figure 10 shows a classification tree or dendrogram where each node beneath the tree represents a coil from group B

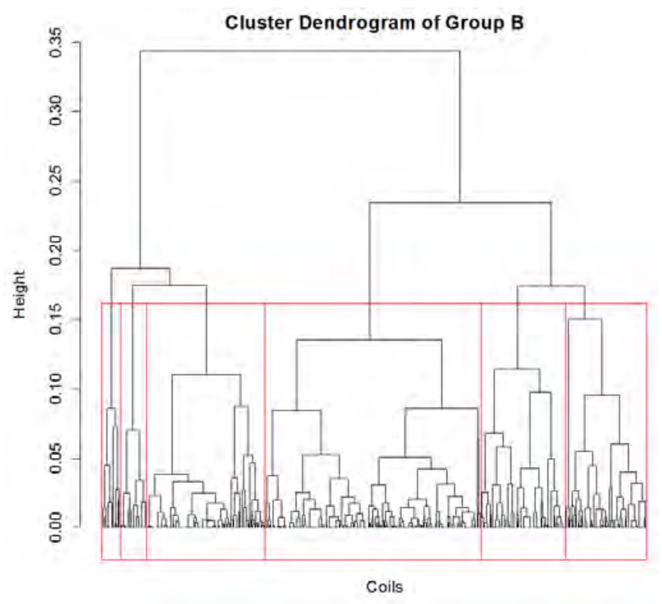

Figure 10. Dendrogram of Group B formed from hierarchical clustering with six clusters

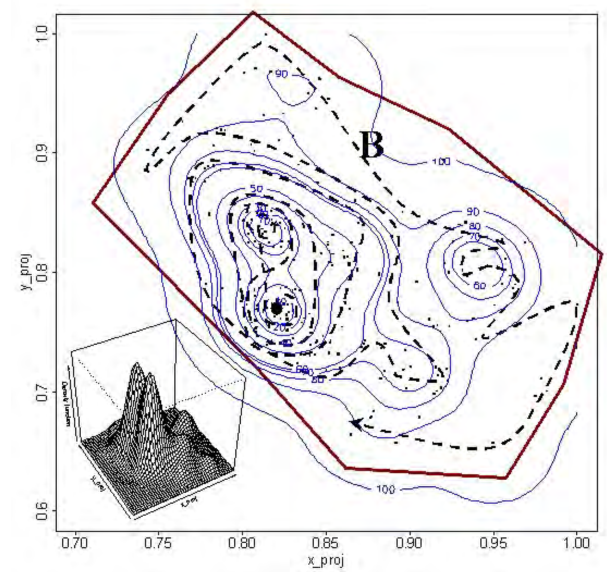

Figure 12. Local scheduling method applied starting of the greatest density in zone B

and each straight line represents the grouping of two clusters positioned by a Euclidean distance equal to the “height” of that straight line. The main advantage in using this type of graph is that the search for subgroups can be automated such that each individual coil does not exceed a determined distance. Partitioning into a given number of set of coils is found by merely cutting the dendogram at an suitable height. Also, abrupt jumps between clusters can be predicted.

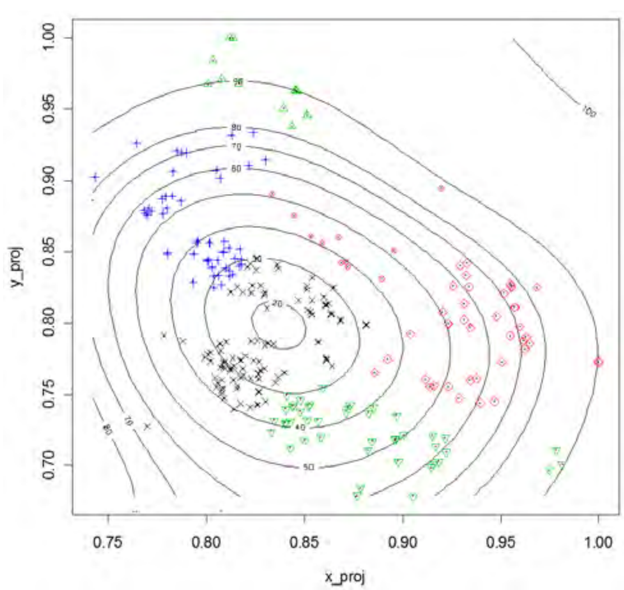

Figure 11. Different subclusters into group B

In Figure 11 are shown 6 subgroups whose Euclidean distance between coils does not exceed 0.15 and are distributed within a bidimensional space. The final scheduling is made automatically for each one of the defined subclusters according to one or several of the parameters employed: width, thickness, chemical components of the steel, target temperature, etc.

Once the local scheduling is made, it is necessary to verify the number of times that it surpasses a defined distance (number of gaps), as well as the maximum distances obtained between ordered coils. If the number of gaps is big or the distances between consecutive coils great, the human expert can take different courses of action until the results of each local scheduling are optimal: i.e. modify the contours that define the groups, divide or fuse groups, choose another distance of clustering, etc.; or by means of techniques widely known: mathematical models, TSP, heuristic techniques, functions relating several variables, etc.

One of the techniques that yields the greatest results consists in beginning the classification by starting at the point where the greatest density of coils exists (top of the mountain of densities) and continuing downward with those points that are less dense (see Figure 12). The process is analogous to descending from a mountain, starting at the peak and the ending at the foot.

Finally, once all of the groups are ordered, those coils that could not be classified in any group can be eliminated, ordered separately, or included in some of the already existing groups.

IV. Results

A. Analysis of a previous historical data using the proposed methodology

The first interesting results arose when analyzing the projection of the 14 chemical components of the coils (C, Mn, Si, S, P, Al, Cu, Ni, Cr, Nb, V, Ti, B, N) for each one of the coils from previous scheduling and upon comparing them with the results obtained after the galvanizing process.

The use of the created map allowed, with a single look and an objective form, the groups of existing coils to be determined as well as to detect those coils whose chemical compositions were completely different. Figure 13 presents the non-linear

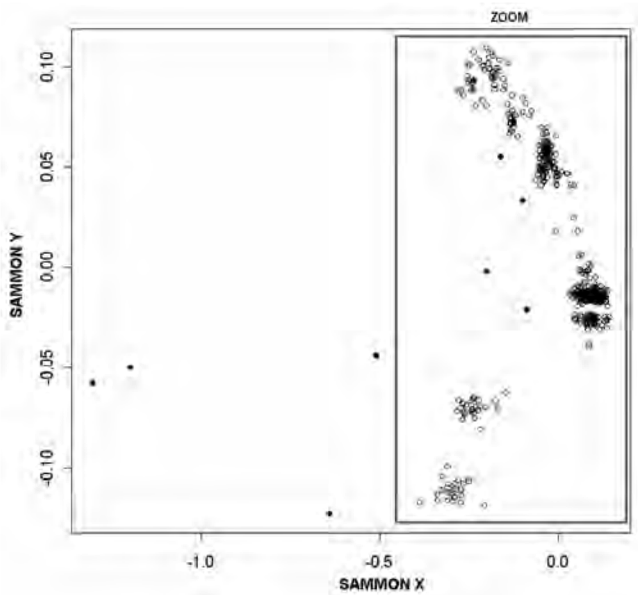

Figure 13. Sammon coils projection according to chemical composition

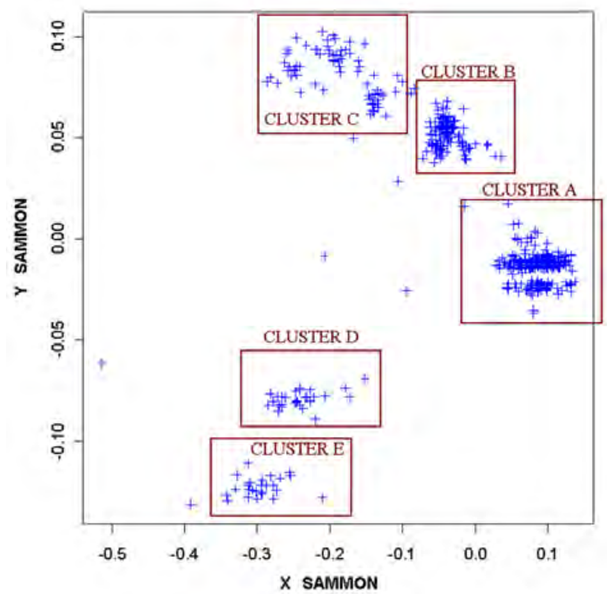

Figure 14. Groups of coils according to the chemical composition of the steel

Sammon projection according to chemical composition and outliers coils that clearly appeared projected separately from the others. In addition, by extending the right part of the map, two main groups (cluster A and B) and three secondary ones (clusters C, D and E) are defined (see Fig. 14). This map can easily be used to classify new coils in one group or another. The method we present is expected to become a useful tool in HDGL applications as Figure 14 shows with 6 groups generated by clustering the coils.

B. Decreasing of unexpected situations and process interrupts

One of the most important problematic events, that worries to the engineers, happens when the industrial process of unexpected way is interrupted such as: breakage of the band, desaleaning, failures in the system, etc.

However, the main advantage when using the proposed methodology is observed when we compare the distances between consecutive coils within the scheduling, since it can be used to help in the prediction of potential problems in the process.

One of these possible causes that can be attributed to problems in an HDGL is produced when one of the welded coils that forms a strip consists of a steel with mechanical characteristics different from the others. Thanks to the use of the map, the expert can easily detect the presence of two consecutive coils with different steel compositions that are going to be processed one after another one. Also, the map can serve as a useful tool to visualize in each moment the type of steel in the coil that is being processed.

The system can also be used to detect when a cross-section differs substantially from the coils that precede and follow it, or has a defective weld, etc.

Another important problem is the breakage of the band. This event is one of the most dangerous contingencies by the high economic losses that produces. These fundamentally must to the lost time in removing the defective band and feeding the line with a new band, as well as, by the lost material and the deterioration that takes place in the machinery. The proposed methodology can help to avoid this event by detecting all strips with mechanical characteristics very different from the others.

C. Two cases of study with problematic events with chemical composition

In Figure 15, are shown two cases of potential, problematic events is shown a case of potential, problematic events due to the inclusion of a coil with a steel different from the others within scheduling. Clearly, one can appreciate the utility in measuring and charting the chemical composition of the steel coils which are involved in the industrial process.

D. Results of the Experience

As has been mentioned, this methodology takes into account not only the chemical parameters of the steel coils, but also the dimensional parameters (thickness and width), target temperature, and other parameters of the process.

In the tests, the following parameters of each coil were included: width and thickness, chemical composition of the steel and desired final temperature; all of them properly weighted.

Introducing the database composed of $2,436$ different coils, a nonlinear Sammon projection was made by obtaining a map similar to the one of Figure 9.

The handling of the map of projected coils was very user-friendly due to the following reasons:

- The selection of the different groups from coils was extremely simple.
- It allowed the expert to detect those coils with parameters which differed greatly from the others.
- It helped to classify new coils easily within the process.

Once the groups of coils were selected, the scheduling for each one was generated semi-automatically according to hierarchical clustering. The results were such that each group was easily ordered according to the desired requirements. The number of gaps between coils was considerably reduced, as well as maximum distances between them. Even in the presence of a great number of gaps or distance between coils, this methodology proved highly effective in generating smaller groups to accommodate the gaps, and in adapting to the contours of greater distances.

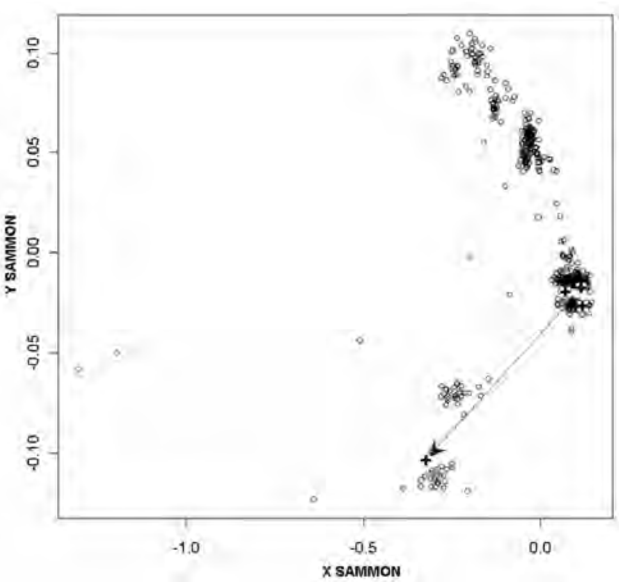

Figure 15. A dangerous hypothetical event due to the presence of a coil from another steel family in scheduling

V. Conclusions

This article presents a successful experience in the use of an MDS to generate bidimensional maps from the multitude of parameters that factor into the process of the creation of scheduling within an HDGL.

The use of these bidimensional maps and the dendrograms allows one to graphically group the coils with the least distance between one another, thus ensuring that their scheduling presents no significant problems.

An iterative process consisting of the following steps was proposed: projecting the coils according to the parameters selected in a bidimensional map, defining the groups of coils with the closest distances between them, selecting subclusters using hierarchical clustering and separately ordering them according to algorithms of already known scheduling.

In this way, lists of safer coil combinations are obtained, abrupt jumps between consecutive coils are reduced and potential problems spotted before occurring.

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