Measuring the performance of field-services through support vector machines (SVM)

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Keywords PMS • performance management system • field services • SVM • regression model

Abstract

Today, most practices used for capacity planning and operations management in field service systems are outdated and overly simplistic. This paper presents an innovative method for the development of a performance management system (PMS) to plan and control the work of large and dispersed field force. We rely on data mining techniques such as support vector machines (SVM) to predict the time required to perform different kinds of field interventions. We have applied SVM techniques on a large amount of real data that we purposively select, extract and elaborate from the database of a case study company, to develop a regressive model. We then use this model to predict the target (expected) performance of each field technician and customer job, and to compare them with the achieved (actual) ones, in order to detect anomalies, organisational flaws, opportunistic behaviours, and any out-of-control situations that may require detailed analysis from the field service managers. Although this approach has been validated using data from a company that provides field services in the multi-utility industry, we believe that the application of SVM algorithms can bring benefits in manifold contexts.

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1. Introduction

The goal of field service managers is to provide the best services at the lower cost ((Watson et al. 1998; Y.-T. Lin and Ambler 2005; Jose, Kumanan, and Venkatesan 2015), by efficiently managing a network of field resources (Belmont et al. 2010). Meeting this need is really complex, because factors that are either endogenous or exogenous to the firm can affect the field performance. Unknown situations may continuously arise and influence the time required to field technicians for traveling to the service point, for task execution, for quality control and data debriefing. Other factors that are critical in field service management concern the gap between the skills mastered by the field force, and those required to perform field interventions, as well as the vastness and characteristics of the area to be served (Tang et al. 2008). In certain cases, the field service network is required to specifically respond to each service demand with a performance that differs customer-per-customer (Hertz et al. 2013). In recent times, field technicians have been equipped with mobile technologies (Agnihothri et al. 2002), so they can receive information pertaining the work to be done and register field data about completion and detected problems (Y.-T. Lin and Ambler 2005). As far as company database becomes populated by field data, managers can leverage data warehouse and Business Intelligence applications to get analytics and performance statistics. These insights are used to support planning and control activities, as well as improvements to the field service network. For example, Watson (Watson et al. 1998) proposes an analytical model to estimate the response time – i.e. the time from the moment when an assistance call arrives until the moment when the technician starts to execute the field service – with the service level agreement (SLA) – i.e. the response time agreed upon with the customer. Using simulation models the service manager can determine the system sensitivity to specific management policies, and determine the best actions to take; however, this implies to have *a priori* knowledge about the network dynamics that only in-depth studies of the field processes can bring. In addition, simulation models need accurate input data, and require great efforts to be validated and updated. In particular, updates should be the more frequent the more new services and procedures are introduced, thus making their use very cumbersome in some situations (Hertz et al. 2013). In sum, the variety of factors that affect the field service performance as well as the lack of appropriate reference models can make extremely complex to set performance control procedures based on analytical, statistical or simulation models (Metters and Marucheck 2007). As a result, it is said that most of the methods used for planning and control of field service network are "outdated and overly simplistic" (Hertz et al. 2013). Therefore, there is the urgent need “for rigorous study to guide service managers in improving design, competitiveness, efficiency and effectiveness of service delivery, both at the firm and industry levels, has never been greater " (Metters and Marucheck 2007).

In this paper we focus on this issue, and suggest a method to detect opportunistic behaviors, system flaws and situations in which the actual performance is not in line with the manager expectations (Finke et al. 2012). Among the alternatives to the adoption of simulation models, statistical-engineering and analytical models, we propose the use of machine learning algorithms. In particular, we develop a support vector machines (SVM) regression model to predict the target performance, and then to compare the predicted (*expected*) performance with the real (*actual*) one. Therefore, our research question can be states as follows: can SVM algorithms be efficiently and effectively used to determine performance benchmark, and facilitate monitoring and control of workforce in field service network?

In line with the Design Science Methodology (Peffers et al. 2006), this research aims to develop and test the model with real data in a real environment, using a typical case-study of a firm that provides field services in the multi-utility industry. Therefore, the paper is structured as follows: firstly, we introduce some key-concepts on SVM, to better characterize the scope of this research. Then, we explain the approach we used and provide some insights on the case study. Last, we show and discuss the research findings, together with some remarks and research avenues.

2. Background

2.1. Support Vector Machines

Support Vector Machines (SVM) are a specific kind of machine learning algorithms. Grounded on Statistical Learning Theory (Grippo and Sciandrone 2003), SVM can be used for classification, regression and other machine learning tasks (Chang and Lin 2011). Introduced for the first time since the early 1990s (Boser et al. 1992; Cortes and Vapnik 1995), they owe their success to their ability to transform the theory of machine learning – that is making computers able to compute and learn from data (Sharma 2014) – into practical tools that can be fruitfully used to solve real-life problems (Vapnik 1999). The purpose of a SVM algorithm is to produce a model – i.e. the "machine" – which, once appropriately trained, can predict the target values (or *labels*) associated with a set of input data (test data), of which only some attributes (*features*, or *patterns*) are known (Hsu et al. 2003). This is exactly what makes SVM a useful tool among Data Mining (DM) algorithms, whose aim is basically mining within some business data, to discover previously unknown relationships and thus gain valuable insights value for the company (Hand 1998). As pointed out by Padhy et al. (2012), DM is crucial in business management, as it allows to identify patterns and features among business data, answering questions faster than traditional tools (Pechenizkiy, Puuronen, and Tsymbal 2005; Silwattananusarn and Tuamsuk 2012). Generally, the choice about which DM algorithm should be use is primarily related to the purpose of each study – that is the information needed by the end user – and the type of data set available. By comparing the results obtained applying SVM algorithms (Chang and Lin 2011) and other 25 methods (16 of classification and 9 of regression) on diverse data sets (respectively, 21 datasets for classification and 12 for regression), Meyer et al (Meyer et al. 2003) conclude that, although it is not possible to dictate that there is an overall and clear superiority of one method against the others, SVM are generally among those algorithms that return the best results for each kind of problems and data sets.

Alike other DM algorithms, SVM can be used to solve different kind of problems, such as *classification* and *regressive* problems (Fayyad et al. 1996). In particular, classification or *pattern recognition* deal with the construction of models that analyze and classify a certain datum within different classes; regression models aim at determining an analytical function that approximates an unknown function, of which some representative target pairs – i.e. the function value – and some pattern – i.e. a set of parameters that characterize the function itself – are known. SVM regression models usually require complex model training, through which the predictive model parameters are determined on the base of a reference data set (Grippo and Sciandrone 2003). The training process is critical as it determines the model's capability to a large extent, i.e. the effectiveness in providing correct answers to new input data that are not included in the training set. For this reason, it is crucial to find the right combination of parameters to set a model that is not either incapable of describing with sufficient accuracy the phenomenon of generating data (*underfitting*), nor able to perfectly interpolate the training data to the detriment of the generalization capacity (*overfitting*) (Grippo and Sciandrone 2003). In order to find the optimal combination of parameters, the models obtained with different combinations are tested on a different test set of which the values that the model should predict are known; when prediction errors of the test set reach a minimum, the corresponding combination of parameters is chosen as the optimal combination.

In this paper we study the effectiveness of SVM regression models to predict time of field interventions, and thus set the line of demarcation between acceptable and not acceptable performances. Setting this line is really cumbersome, and service managers of different industries, as we explain in the following section, could have great benefits from this kind of application.

2.2. Field Services

For Agnihothri et al (2002), service organizations can be divided into two major categories: facility-based and field-based. In a facility-based service, customers access the service facility while in field-based service, it is the responsibility of the service provider to provide service to people and/or their possessions, located at a customer's site. In the case of field-based services (hereafter, field services), the company can provide on-site customer services or remote services and help desk through some contact channel (e.g. phone, chat, web, call center). Field- services could further be divided into three categories: pick-up and delivery services such as mail services and garbage collection; emergency services such as police, fire and ambulance; and after-sales services, such as installation, maintenance and repair. These latter are purposed to provide customer and technical assistance to consumer product and industrial equipment. It is possible to identify three broad industries where after-sales services take place: a) capital equipment, such as office computers and equipment, medical devices, industrial equipment, vehicles, etc.; b) consumer goods, such as domestic appliances, personal computers, home care/surveillance devices, etc.; c) utilities, that include telephone, electricity, gas, water and cable television services for installation, configuration, contract activation. This paper deals with field services, with particular reference to any services that employ appropriately skilled and equipped personnel to deliver the service directly on the field, usually at the customer's premises or in any other convenient location. Considering the examples given in the previous paragraph, our case study has been chosen within the utility industry. In the next section we discuss the reasons behind this choice and present the case.

2.3. Case study

As it was previously introduced, our case study is a mid-sized company providing field services to big gas and water distribution companies. These latter have basically little or no field force, focus on marketing, commercial and administrative activities, thus usually outsource most operational activities - such as infrastructure maintenance, metering installation, periodically consumption reading - to third parties. The case company, in particular, employ a field force of more than 200 field technicians, that provide field services such as meters reading, installation, maintenance and substitution of smart meters. In addition, they intervene for closing those utilities that went into arrears, as well as for re-opening them after due payments are received. The mentioned services greatly differ in terms of required qualifications and skills of the field force, as well as for the service levels that is imposed by the gas or water company, which are the paying customers of our case studies. To respect the service levels, the team of account managers of the case study company is responsible of defining the weekly work plan of the field force. Each account manager, in fact, is responsible of the operational performance of a large group of field technicians, as well as of the financial results of the jobs that they are in charge of delivering. As a result, they have to comply with the requirements of contractual agreements, and at the same time keep operational costs the lowest. To this aim, they notably resort to their experiences, as it is said that these are ill-structured problems that can hardly be solved by analytical algorithms (Y.-T. Lin and Ambler 2005). This situation is indeed typical of manifold field services. For instance, in the case study company, planned tasks (such as smart meters installations) are assigned to the field force on a weekly or daily basis, on the base of their skills and of the operational area. Unplanned requests that may instantaneously arise (e.g. reopening a previously closed meter as due payments are received) are thus superimposed, trying to not upsetting the regular work program of the field technician. Usually, technicians are equipped with a Personal Digital Assistant (PDA), i.e. a mobile device that is used to communicate and exchange information pertaining the service program. In addition to visualizing the personal schedule, field technicians can provide field data that demonstrate to the customer the quality of the work done. For example, when delivering meter reading services the field force is asked for taking a photo of the meter's display, that is then stored in a company database. In addition, mobile technologies are used to collect data that characterize the progress of the daily program, such as the completion of field interventions, the picking up of field materials, tools or parts from the warehouse, and to register the length of unproductive activities such as travel time and lunch break. In some situations technicians are free – to a certain extent – to arrange their work program to better meet some work specifications or environmental conditions. Conversely, in some other cases it is mandatory that they follow precise procedures and schedules. In other cases – namely "services on appointment" – they have to respect appointment times that are usually agreed by the call centre. In any case, there is no one that directly controls their activities, and it happens that only technicians – nor managers – are aware of particular informations (e.g. the expected time to reach the points of service under given traffic conditions, the expected time to deliver field interventions, the preferences about the meeting times in case the intervention requires accessing to the customer's premise) that largely affect the progress of the daily schedule. This is the reason why the field force is often trained to take decisions autonomously, such as choosing to anticipate or postpone some interventions to the next day. This autonomy, along with the absence of direct control, implicates that account managers need tools to control the conduct of their field force, to prevent and check for unethical and opportunistic behaviours. Therefore, there is a great need of performance management systems that facilitate: 1) evaluating the performance of field operators in relation to the different activities/services they are assigned to; 2) detecting and showing rapidly any anomalies among the achieved field performances (i.e. actual against expected performance); 3) estimating the variances in time and costs, in comparison to the targets, reached by the different contracts. These control objectives are hard to put in place, as both measuring the performance gaps and detecting anomalies are greatly affected by the logics behind the definition of what should be actually expected, as the right performance, given the conditions in which the technician is requested to work. Due to the heterogeneity of the provided services as well as to the uncertainty of the environmental conditions, it is rather questionable to use analytical/engineering model for the mentioned purpose. For instance, the company has actually tried to use a standard time performance for the activities of a similar type, that was based on the service levels agreed upon, but it failed because of the variability induced in field operations of the same kind by a lot of endogenous factors. In the next section, building on the premises of the Design Science methodology, we show how this problem could be overcome using SVM algorithms.

3. Research Methodology

The research of this paper has been structured according to the Design Science methodology (Peffers et al. 2006). The following paragraphs describe how we applied this approach in the case study. It is worth to mention that the steps that follow should not be seen as a rigid sequence. Instead, it was crucial to move forward and backward between the different phases when the result obtained was considered unsatisfactory.

3.1. Problem identification and motivation

Company managers need to control the conduct of their field force and consequently evaluate the cost/time variances (e.g. extra budget, delays of the work program), and compare the achieved results to targets and terms established by the contract. The field force could put in place some opportunistic behaviors, diminishing the efforts they put in their field activities. They could also change the criteria they use to organize their work, in case they autonomously take some decisions. Therefore, the managers need to establish which is the right target performance, for each of the assigned task. As said, analytical/engineering models can hardly be employed for this aim, and there is the need of finding new methods that are rather efficient and not simplistic, as they have to consider the travel time to move from one service point to another, the characteristics of the territory – (e.g. for instance urban or countryside), and any other conditions that affect a timely performance (e.g. the intensity of the road traffic on the rush hours, and so on).

3.2. Objectives of a solution

The solution should allow to determine a target performance for each activity, starting from the field data collected by the technicians with mobile technologies – that we suppose can be made available in the company database. As said, such a target should necessarily consider as much aspects as possible that may influence the work organisation, because the aim is to ascertain as much objectively as possible the conduct of the field operator so to enable the account manager to justify any corrective actions that are focused to prevent or reduce opportunistic behaviors.

3.3. Design and development

Our research focuses on the development of a regressive model that can be used to determine the activity performance targets on the basis of a properly defined input data set. This is in line with the mentioned needs. We use SVM algorithms whose aim are – as said - to produce a model that, once appropriately trained, is capable of predicting target values associated with a data set in which only the corresponding features of the target values (*labels*) are known. In addition, it has been demonstrated that SVM are really effective in manifold contexts (Meyer et al. 2003). We demonstrate the validity of this proposal through a case study. Using real data of the case study database, we develop and train the SVM model according to the following steps:

1. Definition of how the target performance of field interventions should be assessed. The literature shows that the performance of field interventions can be estimated in different ways, but that most of them use the concept of "cycle time" (Agnihothri et al. 2002; Tang et al. 2008). This corresponds to the sum of the task time with the travel time. These are respectively the time requested to a field technician to perform a given task, and the time it takes to reach – once finished the previous activity – the site in which the next task has to be provided. Analytical models usually distinguish the specific contributions of both task execution and travel time, since these times are likely influenced by different factors. For instance, labour productivity is influenced by the type of the task to be performed and by the gap between the skills mastered by the technician and those required. For the mentioned reason, we use in our case study the cycle time of each field intervention as the reference performance. This value can be influenced by the following factors: the service type (e.g. meter reading, meter substitution, etc.); whether they are activities with or without particular time constraints (e.g. service by appointment, or massive readings that do not require to access to the customer apartment); the kind of contract/scope in which they are executed, at least differentiating between gas, water, etc.; the outcome of the field intervention, that in the case study can be set to positive, negative, or absent (this latter only for appointment services); the age of the field technician, to estimate how much she/he is experienced; the distance traveled; the accessibility of the counter, that we can easily discriminate between totally accessible, partially accessible, etc.
2. Use of extraction, transformation and loading (*ETL*) process, to obtain the data from the company database. It is necessary to clean and prepare the field data, since usually the raw data stored in the company databases are of disputable quality. Starting from the information that we need to elaborate to calculate the target performance, we identified the data sources from which the requested information could be obtained (Bracchi et al. 2005). It is crucial that the definition of target data is done in collaboration with those that acknowledge the business process (e.g. the service manager, the account managers), whereas the definition of the source data with those that acknowledge the structure and information stored in the company databases (e.g. IT managers, data managers). It is not said that once defined the target data, the corresponding source data can be immediately available. In this case, the process iterates until it source data are available, and they allow calculating target data that are good proxies of the field performance. Source data were then extracted by means of SQL queries, that we specifically built with the help of IT managers. A careful analysis of source data related to different periods and jobs allowed to evaluate their reliability and adequacy, and to sanitize extraction errors. This laid the foundation for the next phase, in which source data are transformed into target data and stored in a specific datamart. In the case study, the mentioned transformation was executed using a Python script, specifically created to upload into the mart all the data pertaining to operative and not-operative activities performed by field technicians in the period of analysis. This datamart also serves to extract the input data for the SVM model, and to check exactly what tasks technician did when the SVM detected some anomalies about their performance.
3. On the base of the data available in the datamart, the characteristics that influence the cycle time are evaluated in order to set up which attributes should be used for the development of the SVM model. The attributes used in the case study are listed in Table 1

Attribute name	Attribute possible values	Description
Service type	Meter reading, meter substitution.	It defines the service typology.
Operation type	Massive, on appointment.	It defines whether the activity is set to be done at a particular hour of day (due to the appointment previously set with the customer) or the operator is free to decide at what time she/he can do the planned activity.
Outcome	Positive, negative, absent.	Positive: task is positively concluded according to what prescribes the contract procedure. Negative: task is not positively concluded according to what prescribes the contract procedure Absent: the customer with whom the call centre has set an appointment is not present. This attribute is different from the others because it is valued only when the operation is done but, based on the historic data, we are able to predict it separately from the SVM analysis.
Type of utility	Water, gas.	The substitution of a gas meter has to follow rigid security procedures, differently from the substitution of a water meter, so it influences inevitably the execution time.
Contract/Commission	(All the possible companies with which the company has stipulated a service contract).	Different contracts can require different operation procedures (e.g. for meters reading sometimes the customer requests a photo of the meter, in some other it does not).
Meter accessibility	Totally accessible, partially accessible, not accessible.	It depends on the meter location: if it is located in a manhole, we expect a higher cycle time if compared to meter in open air.
Distance (m)		The distance between a meter and the next one for which has been planned to make the operation.

Table 1 Attribute names used to characterize the cycle time for the SVM analysis; there is also specified possible values they can assume with a brief description of how they can influence the cycle time.

4. Definition of a statistic that is representative of the performance, to be used for training and validation of the SVM model. This is consistent with the SVM theory, as training must be supported by univocal relationships between attributes and labels. In the case study, after manifold discussions with the account managers and the managing director of the business we decided to use as the reference performance the median of the cycle time obtained by grouping, from the data record, a significant number (i.e. +30) of activities having the same attribute values.
5. Selection of jobs/periods for which we need to extract data and calculate the previously defined statistic. This was crucial because not enough informations were available in many cases/jobs/contracts. If not properly managed, the validation of the SVM model could have been notably hindered. Given the intense business activity and therefore the data at our disposal, a month extraction of the selected contracts was considered sufficient to achieve the needed data.
6. Development of the SVM regressive model. As said, we decided to use the LibSVM open source software (Chang and Lin 2011), which is actually among the best SVM software (Min and Lee 2005; C.-H. Lin et al. 2008; Wang and Lei 2011; Chavhan et al. 2015; Zhang et al. 2017). LIBSVM applications are manifold: bioinformatics (Fanet al. 2005), artificial vision (Grauman and Darrell 2005), financial analysis (Kim 2003), to mention a few. A practical guide for

the LibSVM application to classification algorithms is provide by Hsu et al. (2003). LibSVM requires that input data have a specific binary form, which is constituted by the label (e.g. in our case, the cycle time) and pairs (index, features) as many as the value attributes that characterize the performance to be predicted; Categorical attributes (e.g. massive, on appointment) that have no numeric value, must be adequately transcoded into numbers (Hsu et al. 2003). It is suggested that the number of records in the training data set should be limited, but at the same time they should exceed the number of features (Fan et al. 2008). In the case study, it was possible to collect a sample of the previously specified statistic of nearly 1200 records against a selection of 28 features, making this the choice of LibSVM totally appropriate and justified. Once the input data have been prepared, it has to be divided into two distinct sets, one for training (conventionally 75%) and the remaining for testing. However, much attention has to be given to the data used for model training, because this influences the possibility of generalization. In fact, the training set must be as much representative of the benchmarks we are trying to achieve with the SVM model as possible: the previous two phases, choosing the right statistic and collecting a good sample of data, are crucial for this scope.

Once we developed the SVM model, we used the testing data set to identify the optimal combination of the model parameters, and hence its validation. This is discussed in the next section.

3.4. Demonstration

There is no unique method in the literature to demonstrate the external validity of our research, i.e. if a SVM solution can be efficiently and effectively applied to predict the target performance of field interventions from actual data, given that this performance can be measured by cycle times. In addition, the goodness of the results obtained with the SVM model should be checked. In other words, we should verify if the predicted values are consistent with the target performance that, as in the case study, could have been defined in different ways, prior to the application of the LibSVM. To confront with this issue, we use the test set and compare the predicted target performances with those estimated in the test set by the median statistics, on the base of the following variable:

$$\%\ Deviation = (predicted\ target\ performance - target\ performance)\ /\ target\ performance\ \times 100$$

The reason behind the use of this variable is due to the fact that the model cannot guarantee to exactly predict the target performance for any combination of attributes, or rather it may be able to do so but in general with a certain deviation. In this case, we use the relative (%) deviation as cycle times may remarkably vary, ranging from few seconds in the case of massive readings, to several minutes for smart meters replacements.

4. Findings

The results are shown in graphical and numerical forms. **Fig. 1** is a scatter plot, in which each point corresponds to a pair of target performance and its predicted target performance. The black diagonal line is of course the position where each point should be located in case of a perfect prediction. The variable % Deviation, that has been introduced in the previous section, multiplied by the value of the target performance, corresponds to the y-axis difference between each point and the diagonal. By defining threshold values for the% deviation, both positive and negative, it is then possible to visually evaluate how many of the predicted values fall outside the thresholds, i.e. should be considered not acceptable in case we would use them as the performance benchmark. For instance, **Fig. 1** shows the threshold value of ±10% (the dotted sloped lines), and it can be observed how much of the dots (SVM predictions) fall within the area delimited by the two dotted lines. In particular, **Table 2** shows the results obtained in correspondence of multiple threshold values.

Threshold Value (%)	Out-Threshold Predicted (%)
5	64.43
10	36.91
20	11.41
30	3.69

Table 2 Percentage of out-of-threshold predicted values, for different thresholds.

We can see that for a threshold of 30%, the SVM model fails in only 3.69% predictions, whilst for a threshold value equal to 20%, approximately one in ten values of those predetermined through the SVM model should be considered wrong benchmark.

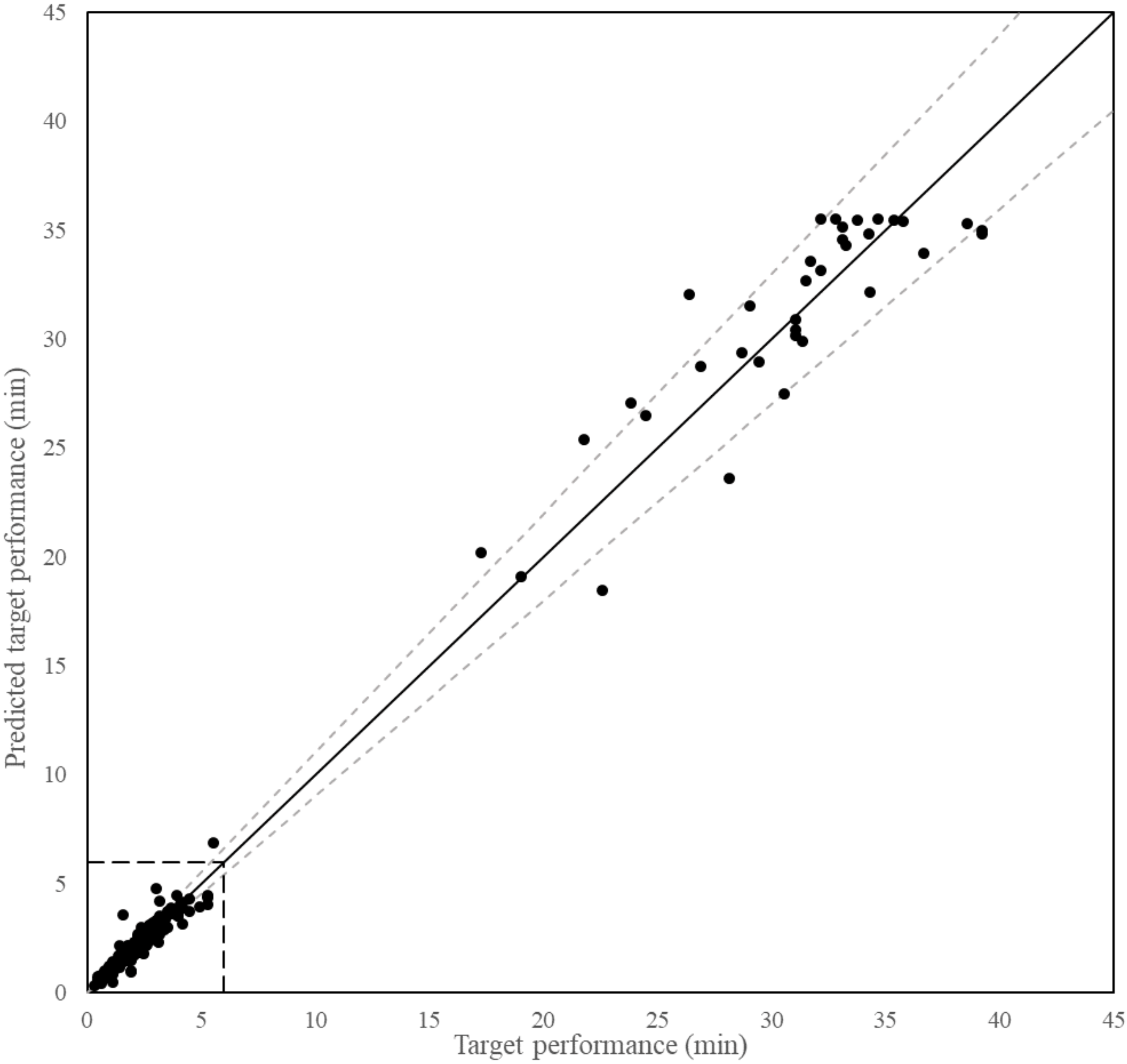

Fig. 1 Scatter plot of target performance (based on median statistics) and of the correspondent predicted target performance using the SVM model; the black points represent the combination of the correspondent values; the dotted slope lines are the limits correspondent to a threshold value of ±10%.

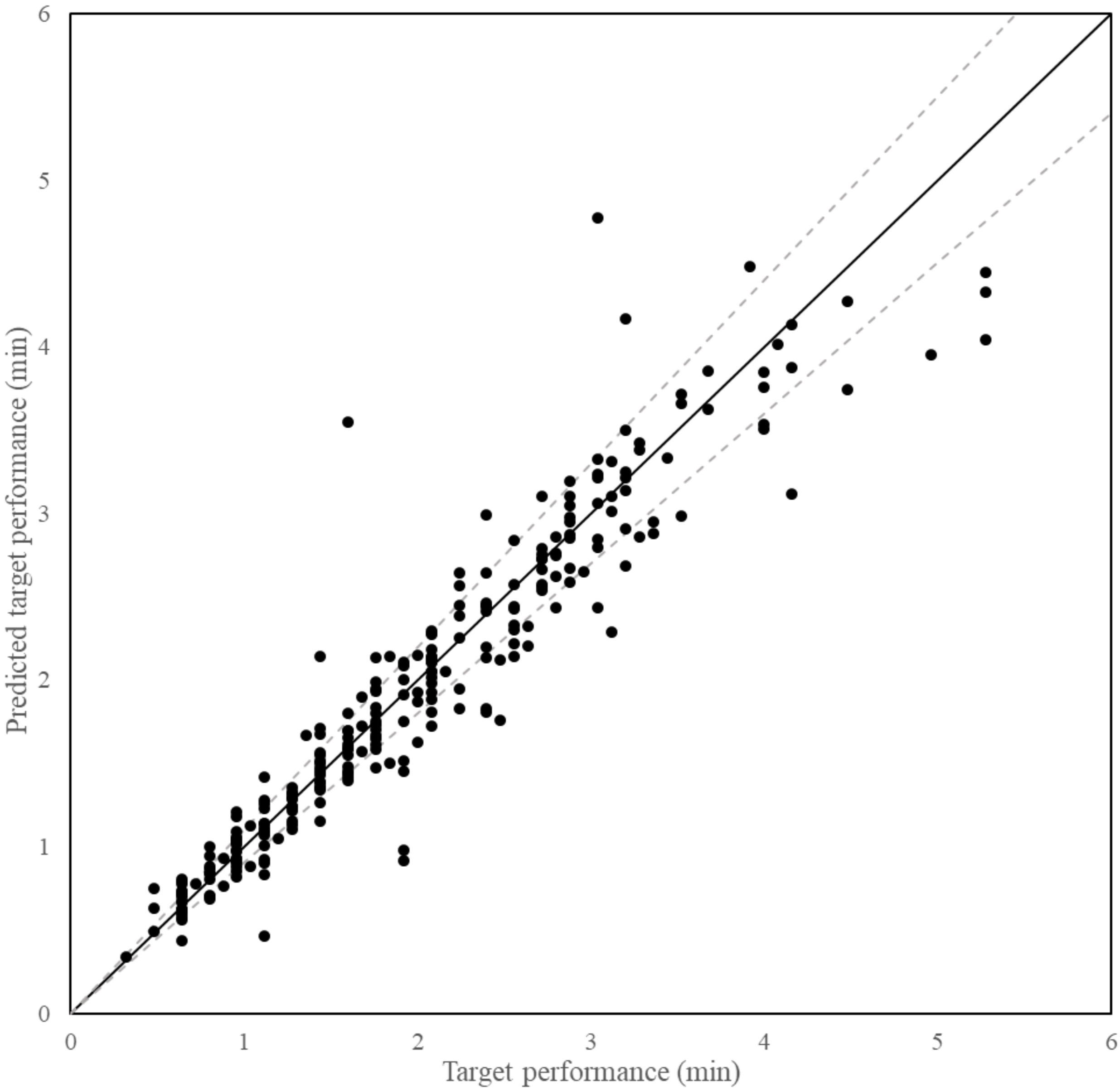

Fig. 2 Zoom of the box in the lower left of Fig. 1, it has the same characteristics but it refers only to the predicted and not predicted target performance that are within 6 minutes of duration.

The box in the lower left of the **Fig. 1** is zoomed in **Fig. 2**; we can see in both figures that although the points are a little bit sparse, most of them – 63.09% to be precise – are contained inside the thresholds lines.

5. Conclusions

Observing the findings, it is difficult to give a unique interpretation of the result of the research. It is evident that, at least for the analysis performed, the SVM model is not perfect in predicting the values of benchmark. Anyway, for a 30% threshold of goodness, the result can be basically considered satisfactory, since in such a situation only the 3.69% of the predicted values would be considered wrong. If we consider the purpose for which we want to calculate a target performance (i.e the detection of anomalies), we can assume that a 30% threshold could be legitimated. As a result, in this situation the SVM model suits to the purpose. It is worth noticing that in its current form, the SVM model we developed can be applied to data that include the outcome of the field activity. In other words, it is not possible to make predictions and comparison as long as the activity itself has not been completed. Therefore, this method can be used only ex post, to control and limit the abuse of opportunistic behaviour. However, it is possible to retrain the model and to use the SVM also for predicting ex ante the target performance, although in this case a new validation is required.

Managerial implications from this research are manifold. Fundamentally, SVM can help detecting idiosyncratic situations. A PMS that leverages SVM can facilitate company managers in controlling relatively large field force, with no need of recurring to analytical models or complex calculation. Moreover, to the best of our knowledge, there are scant applications of machine learning techniques to performance assessment of large set of field service data. Preliminary findings from this research suggest that SVM can easily cope with multi-dimensional data (Kang et al. 2012) and have interesting industrial applications (Widodo and Yang 2007). Main advantage of this kind of solution is that there is no need of knowing or discriminating how the process actually runs, thus opening up room for implementing PMS in dynamic business and complex contexts.

6. Future Developments

The most promising research avenues, in the authors' opinion, concern the development of SVM to enable real-time performance assessment, in order to use SVM for real time dispatching and dynamic rescheduling. It would be precious to evaluate the application of the method in other environments, always using real case studies, in order to compare the results.

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